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AD-A258 646



FINAL REPORT

JOINT TYPHOON WARNING CENTER
(JTWC92) MODEL

Contract N00014-90-C-6042

SAIC Project 01-0425-07-0136

May 1992

SAIC

Science Applications International Corporation

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1. Agency Use Only (Leave blank).		2. Report Date. May 1992		3. Report Type and Dates Covered. Final - Contractor Report	
4. Title and Subtitle. Final Report Joint Typhoon Warning Center (JTCW92) Model				5. Funding Numbers. Contract N00014-90-C-6042 Program Element No. 0305111N Project No. X0523 Task No. Accession No. DN252090 Work Unit No. 94311K	
6. Author(s). R. E. Englebreton*					
7. Performing Organization Name(s) and Address(es). *Science Applications International Corp. (SAIC) 205 Montecito Ave. Monterey, CA 93940				8. Performing Organization Report Number.	
9. Sponsoring/Monitoring Agency Name(s) and Address(es). Naval Oceanographic and Atmospheric Research Laboratory Ocean Science Directorate Stennis Space Center, MS 39529-5004				10. Sponsoring/Monitoring Agency Report Number. CR 028:92	
11. Supplementary Notes.					
12a. Distribution/Availability Statement. Approved for public release; distribution is unlimited.				12b. Distribution Code.	
13. Abstract (Maximum 200 words). The Joint Typhoon Warning center JTCW92 model for the prediction of tropical cyclone motion was developed by Science Applications International Corporation (SAIC), Division 425, Monterey, CA. The project was performed in three phases: database development, model development, and model testing and implementation. The period of performance was September 15, 1989 through July 23, 1992. Progress was interrupted between and within phases due to the incremental nature of funding. Total funding for the program was \$207,102, with \$49,275 for database development and a total of \$157,828 for the last two phases.					
14. Subject Terms. Environmental database, management system, nowcasting, Tactical Environmental Support System 3.0				15. Number of Pages. 90	
				16. Price Code.	
17. Security Classification of Report. Unclassified	18. Security Classification of This Page. Unclassified	19. Security Classification of Abstract. Unclassified	20. Limitation of Abstract. SAR		

May 1992
FINAL REPORT
for the
JOINT TYPHOON WARNING CENTER JTWC92 MODEL

Contract No. N00014-90-C-6042

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DTIC QUALITY

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NTIS GR&I	<input checked="checked" type="checkbox"/>
DTIC TAB	<input type="checkbox"/>
Unannounced	<input type="checkbox"/>
Justification	
By	
Distribution/	
Availability Codes	
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A-1	

CHAPTER 1

PROJECT OVERVIEW

The Joint Typhoon Warning Center JTWC92 model for the prediction of tropical cyclone motion was developed by Science Applications International Corporation (SAIC), Division 425, Monterey, CA. The project was performed in three phases: data base development, model development, and model testing and implementation. The period of performance was September 15, 1989 through July 23, 1992. Progress was interrupted between and within phases due to the incremental nature of funding. Total funding for the program was \$207,103, with \$49,275 for data base development and a total of \$157,828 for the last two phases.

Key SAIC personnel were Charles J. Neumann, Senior Scientist, James M. Shelton, data base and software development engineering, and Ronald E. Englebreton, Project Manager. Dr. T. Tsui of NRL was the Contract Officer's Technical Representative. Other NRL personnel included LT R. Jefferies, R. Miller, and B. Sampson. Mr. C. Mauck and Dr. H. Hamilton of Fleet Numerical Oceanography Center (FNOC) provided assistance during the implementation work.

The JTWC92 is a statistical-dynamical tropical cyclone track forecast model designed specifically for use over the Western North Pacific tropical cyclone basin. The model development was based on Navy analyses (perfect-prognoses) of the Western North Pacific from the period of 1974 through 1988 and designed to run using the Navy's NOGAPS forecast fields. The model will produce forecast positions for a specified tropical cyclone based on the -24 hour, -12 hour and current positions of the tropical cyclone, and deep-layer-mean (DLM) fields for the base time analysis and 12-hour interval forecasts to 72 hours.

The structure of JTWC92 is very similar to that of the National Hurricane Center NHC83 (Neumann, 1988) and the NHC90 (Neumann and McAdie, 1991) models. Supporting documents delivered under separate covers were: Software Design Document, Software Test Plan, and Software User's Manual. The specially designed storm sequenced DLM data base developed in phase 1 was also delivered to NRL.

The following two chapters provide scientific and technical descriptions of the JTWC92 model and a new Western North Pacific Clipper and Persistence (WPCLPR) model development specifically for the JTWC92 model.

References

Neumann, C.J., 1988: The National Hurricane Center NHC83 Model. NOAA Technical Memorandum NWS NHC 41, National Hurricane Center, Coral Gables, FL, 44 pp.

Neumann, C.J. and C.J. McAdie, 1991: A Revised National Hurricane Center NHC83 Model NHC90. NOAA Technical Memorandum NWS NHC-44, 35 pp.

CHAPTER 2

THE JOINT TYPHOON WARNING CENTER JTWC92 MODEL, by Charles J.
Neumann

THE JOINT TYPHOON WARNING CENTER JTWC92 MODEL

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THE JOINT TYPHOON WARNING CENTER JTWC92 MODEL¹

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ABSTRACT

Derivation of the Joint Typhoon Warning Center JTWC92 model for the prediction of tropical cyclone motion through 72h is described. JTWC92 is a statistical-dynamical model in that it utilizes numerically produced 12 through 72h deep-layer-mean geopotential height prognoses in a statistical prediction framework. These height predictors are derived from the Navy Operational Global Analysis and Prediction System (NOGAPS). Additional predictors are obtained from initial analysis of the deep-layer-mean height fields as well as from climatology and persistence. The model was developed in the "perfect-prog" mode using archived NOGAPS initial analysis over the 15-year period 1974-1988. This provided a more than adequate period of record from which to develop the model.

JTWC92 is very similar in structure to the former National Hurricane Center (NHC) NHC83 model which, for a number of years, has been very successful in the prediction of Atlantic tropical cyclone motion. NHC83 has recently been revised by the NHC and designated as the NHC90 model. However, all appropriate NHC90 modifications have been included in JTWC92.

The statistical properties of JTWC92 developmental data were found to be very similar to those of the NHC83 developmental data. Reference here is to correlation fields, partial correlation fields and forecast error. In some cases, correlation fields of tropical cyclone motion vs. geopotential height were virtually identical in the two models even though different initial analyses, different periods of record and different tropical cyclone basins are involved.

This is not intended as a user's manual but rather focuses on the technical aspects of model development. Some pertinent background material is also included. The computer code for activating the model is not included as part of the document.

1. INTRODUCTION

1.1 PURPOSE

JTWC92 is a statistical-dynamical model designed specifically for use over the Western North Pacific tropical cyclone basin. The main purpose of this document is to describe technical aspects of model development. It is not intended as a user's guide and, although some reference is made to the FORTRAN computer code for activating the model, a listing of that code is not included as part of this document.

The structure of JTWC92 is very similar to that of the National Hurricane Center NHC83 (Neumann, 1988b) and the NHC90 models (Neumann and McAdie, 1991), the latter being an update to NHC83. Accordingly, frequent references to and comparisons with those NHC models will be made.

1.2 THE NATIONAL HURRICANE CENTER NHC83 MODEL

NHC83, developed at the NHC over the years 1980-1983 and introduced operationally in 1983, has been very successful in the prediction of Atlantic tropical cyclone motion (DeMaria et al., 1990). However, some correctable

¹This, and an associate document which describes the WPCLPR model (Neumann, 1992), were prepared under Contract Number N00014-90-C-6042.

NHC83 weaknesses were noted over the 5-year operational period 1983-1987 and the NHC modified the model in 1988/1989, at which time it was re-designated as the NHC90 model. The latter was run in parallel with NHC83 during the 1989 season and replaced NHC83 beginning with the 1990 Atlantic season.

1.3 MODIFICATIONS TO NHC83 (NHC90)

The NHC's changes to NHC83 were prompted by factors both internal and external to the model, with the latter factor referring to the National Meteorological Center (NMC) Global Spectral model which provides prognostic geopotential height information to NHC83/NHC90. Although applicable internal NHC83 modifications were also included in JTWC92, and these will be described, it was not considered prudent to include those modifications which were necessitated by changes in the NMC global prediction system. The intent was to drive JTWC92 with the Navy Operational Global Atmospheric Prediction System (NOGAPS) described by Hogan and Rosmond (1991) which has different attributes than the NMC system. Also, some of these attributes may be basin dependent.

2. BACKGROUND

As will be shown, JTWC92 utilizes several classes of statistical models in the overall prediction algorithm. Some general features of these models are relevant to JTWC92 and will be discussed. Also, a brief and pertinent historical perspective on the development of statistical-dynamical models is given.

2.1 CLASSES OF STATISTICAL MODELS

In general, the information (predictors) used by statistical models to reduce the variance of tropical cyclone motion can be grouped into four categories: 1) climatology; 2) persistence; 3) observed environmental data; and, 4) numerically forecast environmental data. Statistical models are often classified according to which of these four types of predictors are contained in the model. (Neumann and Pelissier, 1981; WMO, 1979; McBride and Holland, 1987). CLIPER-class models utilize climatology and persistence. Statistical-synoptic models utilize climatology, persistence and observed environmental data while statistical-dynamical models additionally include numerically forecast environmental data in the prediction scheme.

2.1.1 CLIPER-Class Models - Simple statistical models utilize predictors derived only from climatology and persistence. These can be fixed proportions thereof--as in HPAC (Half Persistence And Climatology) (JTWC, 1989)--or variable proportions of these two factors determined by regression methodology as in Neumann (1972).

JTWC92 utilizes a CLIPER-class model (WPCLPR) as part of the prediction algorithm and Neumann (1992) describes the derivation of WPCLPR. This revises an earlier CLIPER-class model (Xu and Neumann, 1987) for the Western North Pacific basin (WESPAC).

The ability to profitably use such simple models in the operational mode depends on a number of factors including the location of the basin or

portions of the basin and the quality and quantity of the available environmental data. In addition to their operational use, CLIPER-class models are often used as "benchmarks" from which to assess the caliber of other, more sophisticated models. Also, in the best-track² mode, they are used to compare forecast difficulty from one basin to another. (Pike and Neumann, 1987) show, for example, that the use of climatology and persistence has greater utility over the Eastern than over the Western North Pacific Basin.

2.1.2 Statistical-Synoptic Models - In addition to predictors derived from climatology and persistence, models designated as statistical-synoptic additionally include steering³ predictors derived from observed environmental data, typically in grid-point format. Although such models would be expected to outperform CLIPER-class models due to the additional predictive information, operational experience with such models has been disappointing (Neumann and Pelissier, 1981). The explanation here is that the steering information, supplied to the model by the environmental data, is redundant or even inferior to that provided by the actual motion of the storm, the latter being included elsewhere in the model as a persistence predictor.

2.1.3 Statistical-Dynamical Models - The upper-echelon of statistical models are referred to as statistical-dynamical in that they additionally utilize predictors derived from a numerical (dynamic) model. Statistical-dynamical models are considerably more difficult to structure than more basic models.

The difficulty in structuring statistical-dynamical models is mainly associated with the fact that it is generally impossible to obtain n-years of archived output from a numerical model having fixed attributes throughout the n-years. Forecast centers continually strive to improve on the performance of their numerical products with changes to: initialization procedures including "bogussing", initial analysis, model physics, parameterizations, model resolution, etc. (Saha and Alpert, 1988; Schemm and Livesey, 1988; White, 1988, Hogan and Rosmond, 1991). These changes can have dramatic effects on the statistical properties of the model particularly in and around the storm vortex. Since the properties of developmental and operational data must be similar, (Neumann and McAdie, 1991), this is one of the classical statistical pitfalls one encounters in structuring and in the operational activation of statistical-dynamical models.

Another major problem in structuring statistical-dynamical models relates to statistical significance. Typically, output from a numerical model consists of an enormous amount of data. The latter, in grid-point format, provide statistical-dynamical model input and problems arise in assessing artificial skill vs. real skill (Neumann et al., 1977; Shapiro, 1984; WMO, 1979).

A third problem relates to the ability of stepwise screening regression computer programs (Miller, 1966) to efficiently handle the large numbers of predictors associated with statistical-dynamical models. This is a distinctly different problem than assessment of statistical significance.

²The term best-track refers to the accepted track of the storm after a post-analysis.

³The term steering refers to the large-scale tropospheric environmental flow pattern around the storm (George and Gray, 1976; Brand et al., 1981). In statistical models, this is typically inferred from the geopotential height fields.

2.2 STATISTICAL-DYNAMICAL MODELS: HISTORICAL PERSPECTIVE

The earliest known attempt at statistical-dynamical modeling is credited to Veigas, (1966) for the Atlantic basin. Little success was achieved, which, according to the author, was due primarily to the poor quality of numerical weather prediction in the tropics at that time. Veigas suggested the use of what has been referred to as Simulated Model Output Statistics (SMOS) (Neumann and Lawrence, 1975) which is a combination of Model Output Statistics (Glahn and Lowry, 1972) and Perfect-Prog (Klein et al., 1959) methodologies.

The former National Hurricane Center statistical-dynamical NHC73 model (Neumann and Lawrence, 1975) utilized the SMOS concept. The model was quite successful upon its operational introduction in 1973 but was explicitly tuned to the error statistics of the National Meteorological Center Primitive Equation (PE) model of that era (Shuman and Hovermale, 1968). NHC73 was not sufficiently robust to withstand eventual changes (improvements) to the PE model and its operational utility eventually declined.

The NHC83 model (Neumann, 1988b) was specifically structured to avoid some of the pitfalls which eventually caused the downfall of the NHC73 model. In addition, NHC83 utilized many innovations in statistical modeling which will be briefly reviewed in Section 3. NHC83 has been the most successful Atlantic statistical-dynamical model to date and recent performance characteristics are given by DeMaria et al., (1990). As was pointed out in Section 1.2, additional revisions to the model were made in 1990 (Neumann and McAdie, 1991) and it is currently referred to as NHC90.

Additional operational statistical-dynamical models include the Colorado State University Model (CSUM) for the Western North Pacific as described by Matsamoto (1984) and the National Hurricane Center EPHC81 model for the Eastern North Pacific as described by Leftwich (1981).

3. SOME FEATURES OF NHC83/NHC90/JTWC92 MODELS

The Atlantic NHC83/NHC90 models and this JTWC92 counterpart for WESPAC utilize methodology not previously employed in statistical modeling. This includes the use of deep-layer-mean heights fields, temporal averaging of height fields, a rotated grid system and an iterative forecast procedure. These new features will be briefly reviewed; a more complete discussion is given by Neumann (1988b) and Neumann and McAdie (1991).

3.1 USE OF DEEP-LAYER-MEAN HEIGHT FIELDS

Sanders and Burpee (1968) pointed out the advantages of using a deep-layer-mean wind field and demonstrated how to use the data in an operational environment. Although it would have been desirable to use deep-layer-mean winds in statistical-dynamical models, there are numerous problems involved in doing so (Neumann, 1988a).

Neumann (1979) tested deep-layer-mean heights in regards to their tropical cyclone motion variance reducing potential. His study clearly showed that there was more predictive information contained in layer averages than in

Table 1. Assigned weights and standard heights for NHC83/NHC90/JTWC92 deep-layer-mean geopotential height computations. Standard Heights are from Jordan's (1957) mean September tropical atmos here.

<u>Level Number (i)</u>	<u>Level (mb)</u>	<u>Weight (mb/mb)</u>	<u>Weight (W_i) (0 ≤ W_i ≤ 1)</u>	<u>Standard Height (m) (H_i)</u>
1	1000	75/900	0.083333	122
2	850	150/900	0.166667	1539
3	700	175/900	0.194444	3176
4	500	150/900	0.166667	5883
5	400	100/900	0.111111	7593
6	300	75/900	0.083333	9683
7	250	50/900	0.055555	10939
8	200	50/900	0.055555	12405
9	150	50/900	0.555555	14185
10	100	25/900	0.027778	16569
DLM	1000 to 100	900/900	1.000000	6060.5

any single level. Many different methods of computing these layer averages were tested and his conclusion was that the Sanders and Burpee (1968) method of mass-weighting the 10-standard levels from 1000 to 100 mb gave the best results in regard to explaining the variance of short-term tropical cyclone motion. Later studies such as Pike (1985), Dong and Neumann (1986) confirmed these findings.

The mathematical function (f) for computing deep-layer-mean heights for a given location is,

$$f(W,H) = \sum_{i=1}^{i=10} (W_i H_i) \quad (1)$$

where W and H are weighting factors and standard heights, respectively, as specified in Table 1 and the index *i* refers to level. The standard heights refer to the Jordan (1957) mean September tropical atmosphere.

Although Jordan's atmosphere refers to the Caribbean area, this is of no consequence in the computations. The use of departures from normal rather than actual heights is purely a convenience and any standard could have been used. Weighting the tabular standard heights in accordance with Eq. (1) gives a JTWC92 "reference" geopotential height of 6060.5 meters and that quantity was subtracted from all deep-layer-mean geopotential heights used by the model. Operational activation of the model will require similar processing.

3.2 GRID SYSTEM

3.2.1 Grid Spacing - Neumann (1979) examined the utility of various grid-spacings in statistical prediction models. These grids are used to represent environmental data included as statistical predictors in the models. One of his conclusions was that the 300 n mi (556 km) grid spacing used in statistical models of that era (Miller and Chase, 1966) was too coarse and that the optimal present-day statistical model grid-spacing was near 150 n mi (278 km).

3.2.2 Grid Orientation - With the exception of storms initially located near the equator (details to be provided in a later Section), grids are rotated according to the initial motion of the storm over the previous 12 hours. Forecast storm motion within the model is in terms of continued motion along this

(persistence) track or across (at right angles) to the track using Taylor (1982) great-circle map projection software.

The motivation for this grid rotation is described by Shapiro and Neumann (1984). The authors demonstrate that such a system helps to alleviate slow speed bias, a problem common to most statistical models (Neumann and Pelissier, 1981). The authors also demonstrate that the total forecast error was less using the rotated system compared to a conventional non-rotated grid.

Operational use of the NHC83 model over a number of years (DeMaria et al., 1990) confirms that the NHC83 model, indeed, does not have a significant slow speed bias compared to other models. In that the NHC83 model contains many other innovations, it cannot be stated conclusively, however, that the rotated system is responsible for the success of the model in that regard.

3.2.3 Grid Domain - The 150 n mi developmental grid system used in the NHC83\NHC90\JTCW92 models to represent the deep-layer-mean height fields is depicted in Fig. 1. There are two grid domains. In the larger 29x21 system, the storm is always positioned as shown with the grid being oriented as noted in previous Section 3.2.2). The larger grid is used in the early phases of model development.

Stepwise screening regression programs (Miller, 1966) are associated with a considerable amount of matrix manipulation. The number of grid points (609) in the larger 29x21 grid is far too large for efficient computer manipulation of the matrices. Accordingly, the smaller 15x11 grid system depicted in Fig. 1, having 165 potential predictors is used in final development of the model. These smaller grids are also used in the operational mode.

The location of the storm within the smaller grid depends on which of three stratification zones, North, South or Equatorial (see Section 5) within which the storm is initially located. For the North and Equatorial Zones, the grid having horizontal shading is used while for storms initially located in the South Zone, the grid is shifted to the right (vertical shading). The position of the storm in these grids was determined by the correlation (between storm motion and geopotential heights) pattern relative to the storm as well as to the desire to keep the entire grid domain in the northern hemisphere.

The grid rotation remains fixed throughout the 72h forecast period even though the storm heading might change. However, the grid translates with the storm. In the developmental mode of the model, best-track storm positions are used to position the grids throughout the forecast cycle. In the operational mode, a "first-guess" to the these grid positions is provided by the CLIPER model and the initial analysis. (see Section 3.6).

The positions of the grid points relative to the given storm heading and position are based on an approximately great-circle system described by Taylor (1982). Distances between grid points are approximately constant.

3.3 STATISTICAL SIGNIFICANCE ASPECTS OF PREDICTOR SELECTION

3.3.1 Artificial vs. Real Skill - The number of predictors being considered

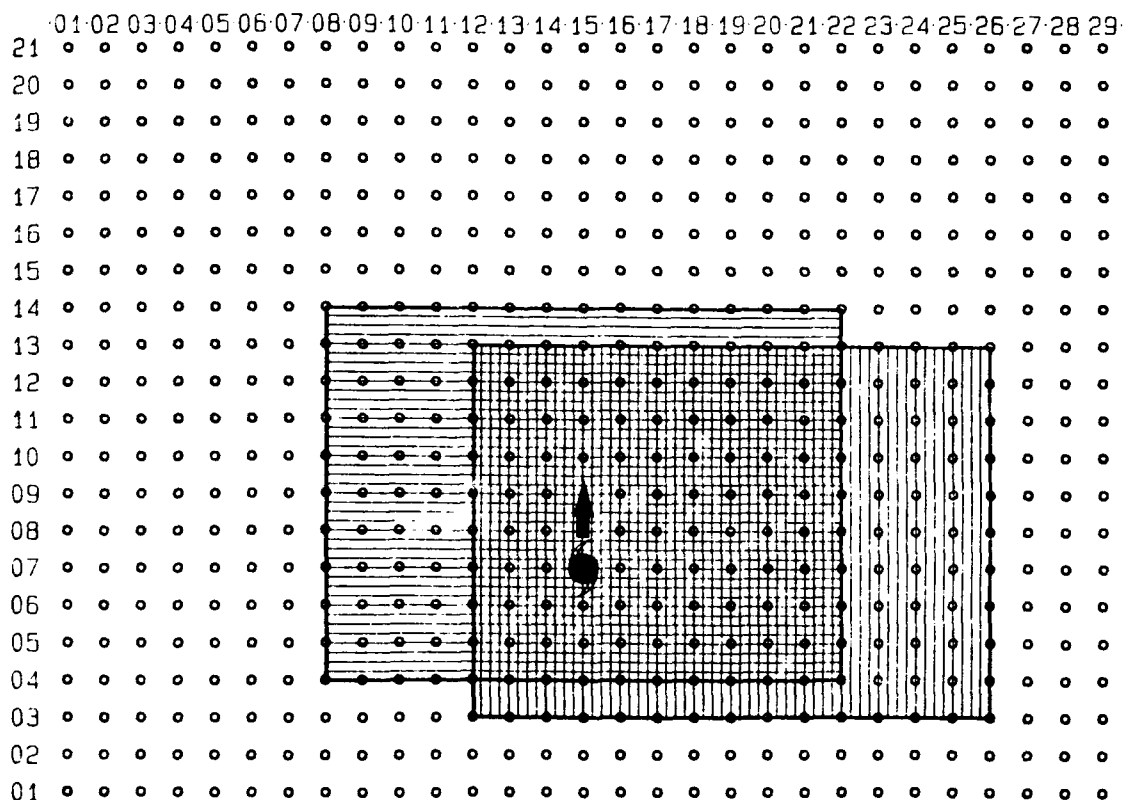


Fig. 1. JTWC92 grid systems. Grid spacing is 150 n mi (278 km) and storm is always positioned at column 15, row 7 of large 29x21 grid, as shown. Position of storm in smaller developmental and operational 15x11 grids is variable, as shown. Except as noted in text, grid is aligned according to the heading of the storm from the -12h position to the current storm position. Which of the two small grids actually used by the model in a given forecast situation depends on the location and motion of storm (see text).

and retained in the NHC83/NHC90/JTWC92 models were governed by findings of Neumann et al., (1977) and of Shapiro (1984). Those authors, using Monte-Carlo simulation methods, addressed generation of artificial skill resulting from the practice of offering a stepwise screening regression program a large number of predictors but selecting only a small sub-set of these for retention in the model. The above studies clearly showed that the statistical models developed at or for the National Hurricane Center prior to the NHC83 era contained far too many predictors.

Artificial skill is also generated by not accounting for serial correlations in the developmental data where cases are typically observed at 12-hourly intervals. To account for this, the effective sample size was reduced according to methodology described by Neumann in WMO (1979).

Using the net reduction in degrees of freedom from serial correlation and from the practice of selecting only a few from a large number of predictors and the further use of a 99% level of statistical significance, resulted in only a small number of geopotential height predictors being retained by the model. As will be shown, only 2 to 4 predictors were retained for a given orthogonal component of motion and a given projection, 12 through 72h.

3.3.2 "Pairing" of Predictors

The stepwise screening regression computer program used here, forwardly selects predictors which maximize the variance reduction between tropical cyclone motion and the geopotential height predictors. Use of the latter, rather than winds, results in "pairs" of heights, located asymmetrically either side of a storm, being typically selected in the first two "steps" of the screening program. These two predictors typically provide for most, if not all, of the variance reduction provided by the heights for the given forecast interval and the given component of motion.

A shortcoming of the forward stepwise screening regression methodology used here is that optimal pairing of functionally related predictors is not guaranteed. The program selects only one predictor at a time and has no knowledge of future predictor selection or functional relationships between or among predictors. This initial predictor becomes "locked-in" and incremental variance reduction (partial correlation) govern the next selection. This presents a problem in that the first two selected predictors may not be optimal insofar as variance reduction and efficiency are concerned.

Neumann (1979) experimented with this problem and concluded that there was a significant gain in variance reduction by providing a priori guidance to the screening program in the selection of the two initial predictors. This was accomplished by noting the variance reduction obtained from all possible forced combinations of the initial two predictors. Although here there was likely some gain in artificial skill, the gain in real skill appeared to be greater.

In general, these "forced" pairings resulted in predictor locations being closer to the storm than would otherwise have been the case. Also, the combined reduction of variance was often large enough such that additional predictors, located farther from the storm, failed to provide additional statistically significant variance reduction.

The forced pairing technique was used in developing the JTWC92 model. However, for the most part, it was not used whenever the technique resulted in predictors being selected closer than three grid-point intervals (450 n mi) from the storm. Experience has shown that predictors located too close to the storm present problems with bogus vortex specification when activating the model in an operational mode. This reasoning was also used in the recent NHC revisions to the NHC83 model described by Neumann and McAdie (1991).

3.3.3 Additional Comments on Predictor Selection - The geopotential height predictors objectively selected for a given forecast interval, say 48h, may not be the same as those objectively selected for adjacent forecast intervals -- in this case 36h and 60h. Experience with other models clearly shows that this can present a problem in regard to the production of an unrealistic meandering forecast track which further leads to forecaster skepticism about the credibility of the forecast product.

To correct for the possible occurrence of this problem, every attempt was made to insure that, for a given orthogonal component of motion, the same

predictor pattern⁴ was maintained for all projections. Occasionally, this dictated a relaxation of the 99% significance level criteria discussed in Section 3.3.1. However, if the significance level dropped to below 95%, no attempt was made to force the same predictor pattern for that particular time period. These rather subjective criteria about predictor locations were established in connection with the revision of the NHC NHC83 model.

3.4 USE OF "PERFECT-PROG" METHODOLOGY

In general, there are three methods for developing statistical-dynamical models: **Perfect-Prog** (Klein et al., 1959), **Model Output Statistics** (Glahn and Lowry, 1972) and **Simulated Model Output Statistics** (Neumann and Lawrence, 1975). Considerations of the advantages and disadvantages of each of these methods (Neumann, 1988b) led to the selection of the Perfect-Prog (PP) methodology for developing the NHC83/NHC90/JTWC92 models. As used here, the essential feature of the PP approach is that actual analyses of deep-layer-mean fields are used to develop the model but numerical forecasts of these fields are used in the operational mode of the model. A requirement here is that both the analysis fields and the numerical model fields maintain similar statistical properties.

3.5 JTWC92 SUB-SYSTEMS

In reality, JTWC92 consists of 5 distinct sub-systems (models) and these are all used in the operational prediction algorithm. A schematic of the sub-systems is depicted in Fig. 2. Each produces a complete forecast through 72h and will be briefly described.

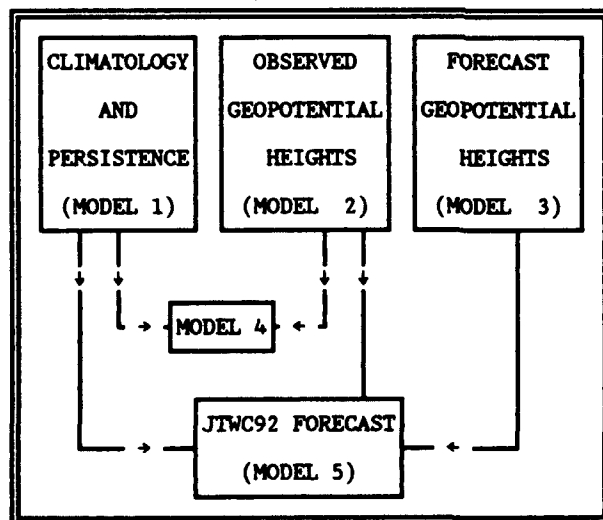


Fig. 2. Schematic of the five sub-systems (models) comprising the JTWC92 model (see text). Each of the sub-systems produces a forecast of motion through 72h.

⁴The term pattern refers to the general rather than the precise location of a grid-point predictor.

3.5.1 Model 1 - Model 1, refers to the WPCLPR model (Neumann, 1992) where predictors are limited to those derived from climatology and persistence.

3.5.2 Model 2 - In model 2, predictors are limited to those deep-layer-mean heights obtained from the initial analysis. It will sometimes be referred to as the **Analysis** mode of JTWC92.

3.5.3 Model 3 - In model 3, predictors are limited to those deep-layer-mean heights obtained from a numerical model. However, in the developmental mode of JTWC92, future observed analysis fields are substituted. This will sometimes be referred to as the **Perfect-Prog** (PP) mode of JTWC92.

3.5.4 Model 4 - Model 4 is a combination of Models 1 and 2. In effect, this is a statistical-synoptic model (see Section 2.1.2). Model 4 is used as a "first-guess" to the forecast in the operational mode of JTWC92 but is not needed in the developmental phase of the model.

3.5.5 Model 5 - Model 5 is the final forecast product. It is a combination of Models 1, 2 and 3. In the operational mode of JTWC92, Model 5 cannot be activated until Model 4 gives the estimated position of the tropical cyclone at each of the six 12-hourly positions, 12 through 72h. In the developmental mode of JTWC92, the best-track is used to obtain these "forecast" positions.

3.6 USE OF AN "ITERATIVE" FORECAST PROCEDURE

3.6.1 Further Comments on the Role of Model 4 - Model 4 is not used in the developmental phase of the model but has an important role in the operational mode. As pointed out above, this role is to provide a "first-guess" to the 72h forecast track. Model 3 requires that the 15x11 grids (see Fig. 1) be positioned at the forecast position of the storm at each of the 12h projections, 12 through 72h. In accordance with Perfect-Prog methodology, the best-track is used to position these grids in the developmental mode of the model.

In the operational mode, Model 4 is used to provide an estimate of these forecast positions. Once this estimate is available, Model 3 can be activated. Finally, having a 72h forecast track from Models 1, 2 and 3 allows Model 5 to be activated.

In that the forecast DLM fields are additionally used in the forecast process, it is logical to assume that the forecast track from Model 5 is superior to that originally provided by Model 4 alone. Accordingly, this initial Model 5 forecast of the track can be used to re-activate Model 3 which, in turn, provides a revised Model 5 forecast.

3.6.2 Optimum Number of Feedback Iterations - The above "feedback" procedure can be repeated any number of times. In most cases, the system will converge and oscillate about a final forecast track within a few iterations but, in other cases, excessive iterations degrade the forecast. The effect on forecast error is primarily on the extended projections. Extensive testing during development of the NHC83 model (Neumann, 1988b) suggests that the optimum num-

ber of cycles is related to the synoptic pattern and the degree to which the estimated average heading of the storm over the past 12h (used in aligning the grid system) agrees with the actual heading. For the NHC83 model, 2 or 3 iterations, provides the lowest forecast errors when the model is activated in an operational mode. In the JTWC92 model, the optimum number of program iterations, based on developmental data, was determined to be three (see Appendix B).

In that the optimum number of iterations might be dependent on the initial analysis, on the numerical prognoses and perhaps on other factors, it is recommended that at least one year of operational runs of the model be used to optimize the setting of the iteration option. This will require archiving the precise input data that were used for the original operational runs.

3.7 TEMPORAL AVERAGING OF GEOPOTENTIAL HEIGHT PREDICTORS

The NHC83/NHC90/JTWC92 models utilize forecast time steps (Model 3) as follows: 0 to 12h, 0 to 24h, 0 to 36h, 0 to 48h, 0 to 60h and 0 to 72h. The 0 to 12h forecast uses predictors obtained from a linear average of the translated and rotated 15 x 11 grids (see Fig. 1) for both the initial analysis (0h) and the 12h forecast fields; the zero to 72h forecast use predictors obtained from an average of each of the 7 translated and rotated grids between zero and 72h. Specific steps followed in augmenting the temporal averaging scheme in the developmental mode of the model are as follows:

(1) For a given initial forecast situation at time T_0 , seven NOGAPS 63 x 63⁵ NOGAPS fields were obtained. These are the initial analysis for the time T_0 and the subsequent analysis at 12h intervals through 72h.

(2) On the appropriate NOGAPS 63 x 63 northern hemisphere DLM analysis fields, the large 29 x 21 grid shown in Fig. 1 was positioned at the best-track position of the storm for the appropriate projection; i.e., the initial position of the storm was positioned on the initial grid, the +12h position of the storm was positioned on the +12h NOGAPS grid, etc.

(3) The large 29 x 21 grids were rotated according to the average storm heading over the period T_{-12} to T_0 , these being obtained from the best-track of the storm. For the equatorial zone (see Section 5.2), the storm heading was always taken as being towards 360°. This grid rotation remains constant throughout the 72h forecast cycle regardless of a likely change in storm heading over the period.

(4) The location of each of the 609 grid points in the large (29 x 21) grid after the translation and rotation noted above was determined from the Taylor (1982) navigational routines. DLM geopotential heights at these points were interpolated from the still larger northern hemisphere 63 x 63 grid.

(5) For the 12h forecast fields, the grids for time T_0 and T_{+12} were averaged. For the 24h forecast fields, the grids for the three time periods T_0 , T_{+12} and T_{+24} were averaged, etc. The 72h forecast fields are an average

⁵For convenience (see Section 4.1.2), this grid was expanded to size 65 x 65.

of all seven grids from time T_0 to T_{+72} . If a missing grid was encountered, a flag was set at the forecast interval.

It should be noted that the grid averaging is accomplished after translation and rotation of the grids. The grid-averaging procedure is somewhat similar to an alternative procedure of providing forecasts in 12h time steps: 0 to 12h, 12 to 24h, rather than 0 to 12h, 0 to 24h, etc. as accomplished here. However, tests on the development of the NHC83 model, indicated that the procedure adopted produced less forecast error on the developmental data. Further comments on the grid-averaging rationale are given in Neumann (1988b).

4. THE DEVELOPMENT DATA SET

4.1 PREDICTORS AND PREDICTANDS

The period of record used in developing the model was 1974-1988. For all potential forecast situations over this 15-year period it was necessary to construct a master file containing all predictors and predictands from the best-track file and all predictors from the DLM grid data. This was accomplished by initially setting up two preliminary files: a master storm data file and a master upper-air data file and then merging these into a single master screening file from which all screening runs were made.

4.1.1 Storm Data File - The preliminary storm data file contained predictors and predictands for each of the verifiable 1974-1988 forecast situations, with the latter term (forecast situation) being defined as:

- Initial wind speed of at least 34 knots (named storms);
- Best-track storm position available at end of forecast interval (12 through 72h) with wind of at least 34 knots;
- Storm positions available at -12h and -24h (needed to activate the WPCLPR model). A requirement for associated storm intensity of at least 34 knots was not necessary for these latter positions.

These criteria resulted in the potential availability of 3495 cases, 1974-1988, when there was a verifiable forecast for at least 1 of the six forecast periods, 12 through 72h. However, concomitant upper air data were not always available for each of these cases.

4.1.2 Upper-Air Data File

In developing the JTWC92 model, archived FNOC Northern Hemisphere initial analyses over the 15-year period 1974 - 1988 were used. Northern hemisphere deep-layer-mean (DLM) fields were produced from archived analyses of each of the 10 levels 1000 to 100 mb, as specified in Table 1. If only a single level was missing from the archived files, 9, rather than 10 levels were used by re-computing the weighting factors. If more than one of the ten levels was missing, the case was discarded.

FNOC Upper-air data were archived on the standard 63 x 63 Northern Hemisphere grid system using a polar stereographic projection, true at 60N where grid spacing is 381 km. The pole position is at grid point I=32, J=32 where I refers to columns 1 to 63 and J refers to rows from 1 to 63. Column 32 is along longitude 80W/100E such that (I,J) grid point (32,1) is at 0.2°N, 80°W.

Some of the NHC83 computer software which was used in developing JTWC92 assumed that the grid system was the standard National Meteorological Center 65 x 65 polar stereographic grid system rather than the 63 x 63 FNOC grid. For convenience, therefore, the grid was expanded to a 65 x 65 version (pole position I=33, J=33,). This was accomplished by keeping the grid values in the boundary rows or columns constant.

It was only necessary to obtain the DLM data on days upon which at least one named tropical cyclone was in existence. Also needed for each initial forecast situation were the DLM fields at 12-hourly intervals through the 72h projection or through the duration of the storm if that were less than 72h. Not all of these required upper-air data were always available.

4.2 MERGED FILE

Whenever there was no missing data, the storm data file and the upper-air-data file were merged. During the merging process, the grid was transformed into the precise time averaged and rotated version needed by the model and as described in Section 3.7.

The final merged file contained 2618 cases, each with at least the potential for a 12h forecast, this amount decreasing to 1427 cases at 72h. This sample excludes a few cases classified as outlier⁶ cases, these having been identified later in model development. This is considered a rather large data set insofar as this type of model is concerned. For each of the 2618 cases, at 12-hourly intervals through 72h (missing data were entered as such), the master screening data set contained:

- Seven geopotential height fields, defined on the 29 x 21 grid system shown in Fig. 1. These fields were for the initial analyses and the 6 "projections", 12 through 72h;
- Positions of storms from -24h to +72h;
- Intensity of storms from -24h to +72h;
- Storm displacements resolved into appropriate orthogonal components;
- Forecast WPCLPR displacements resolved into appropriate orthogonal components;
- Various "book-keeping" items.

⁶An "outlier" is a case that has excessive residual error compared to the other cases.

5. STRATIFICATION OF DATA SET

5.1 RATIONALE FOR STRATIFICATION

Stratifying a developmental data set into common groups of data typically improves on the performance of a statistical model. There are any number of reasons for this. In a rotated grid system model such as JTWC92, stratification is very important in ascertaining that grid points do not fall outside the domain of the grid system. Also important is the fact that storms located south of the subtropical ridge line appear to be controlled more by the ridge itself (i.e., primary grid points are located in the ridge line); while storms located north of the ridge appear to respond more to impulses in the westerlies (i.e., primary grid points are located in the westerlies).

One of the risks of stratification is decreasing the sample size below that acceptable for adequate statistical significance in the zone. However, the sample size here is large enough to avoid this pitfall.

5.2 JTWC92 STRATIFICATION

5.2.1 Initial Two-Zone Stratification - The National Hurricane Center NHC83 and NHC90 models are stratified into a "North" and a "South" zone. Assignment to a zone is based primarily on latitude but also depends on the initial motion. For the NHC models, both developmental and operational forecast errors are less over the South-Zone. This is not unexpected in that storms in that zone move on a slower, steadier track than do North-Zone storms. As an initial attempt at stratification for the JTWC92 model, this same NHC system was used in a preliminary screening run for Perfect-Prog Model 3 (See Section 3.5.3). The results of this test showed, contrary to expectations, that forecast errors over the South-Zone exceeded those over the North-Zone.

5.2.2 Problems with Equatorward Storms - This initial test prompted an investigation into the error patterns of South-Zone storms. It was noted that most of the storms with the largest errors were located in the deep tropics, often south of 10°N where the surrounding geopotential height field is not coupled very well with the wind field. Perhaps more importantly, many of these storms were moving in a direction such that the domain of the rotated 15 x 11 grid (see Fig. 1) was falling well into the Southern Hemisphere. These factors suggested that these near-equator storms would need to be treated separately.

An attempt was made to forecast these storms using Model 1 (the WESPAC CLIPER model) alone. Also, a test CLIPER-class model was developed exclusively for storms located south of 12°N. Although these did reduce the errors on the near-equatorial storms, they were still too high to be acceptable.

As a further test, the equatorial portion of the master screening data set described in Section 4.1 was reworked with the grid rotation held constant. Two versions were structured. One version of the grid utilized the standard zonal/meridional system; in effect, storm motion over the past 12h is set to 360° insofar the positioning of grid points is concerned. Another version was to align one component of the orthogonal system along the 292° average motion of the storms in the near-equator zone (Pike, 1987).

Using these grids with fixed rotation, test screening runs on those Model 3 storms located in the deep tropics were conducted. The test showed that the zonal/meridional system (simulating storm motion towards 360°) gave the lowest errors, with the amount being more typical of storms in that area. Accordingly, the decision was made to use storm dependent grid rotation only on storms initially located outside of the deep tropics.

5.2.3 Final Three-Zone Stratification System - Having made the decision to not rotate grids for near-equatorial storms, but rather to use a standard zonal/meridional system in that area, approximately 55 test predictor screening runs (with a 1% incremental variance reduction cutoff for including additional predictors) were activated. These screening runs used various latitudinal and motion bounds for storms located in a North, South and an Equatorial zone. For each test screening run, a final 72h forecast error on the entire data set without regard to zone was computed and the decision to use the motion and latitudinal bounds finally selected was based on minimum 72h error. Logic for the final stratification system is depicted in Table 2a while the number of cases in each zone is given in Table 2b.

Table 2a. Stratification scheme for JTWC92 model. The term "westerly" refers to storms with the average motion from the -12h storm position to the initial position $\geq 210^\circ$ to $\leq 330^\circ$. Stationary storms are assigned a heading of 360°.

NORTH-ZONE

All storms initially $\geq 22.0N$.

All storms initially $\geq 15.0N$ and $< 22.0N$ and not having "westerly" motion.

SOUTH-ZONE

All storms initially $\geq 12.0N$ and $< 22.0N$ having "westerly" motion.

EQUATORIAL-ZONE

All storms initially $< 12.0N$

All storms initially $\geq 12.0N$ and $< 15.0N$ and not having "westerly" motion.

Table 2b. Developmental data sample sizes associated with final stratification system.

	12-hour	24-hour	36-hour	48-hour	60-hour	72-hour
NORTH-ZONE.....	1169	987	830	686	559	449
SOUTH-ZONE.....	1063	994	915	835	753	677
EQUATORIAL ZONE.....	386	365	350	334	319	301
ALL ZONES COMBINED..	2618	2346	2095	1855	1631	1427

5.2.4 Statistical Properties of Data Sets - Storms located in each of the three stratification zones have widely different statistical properties. Some of these, relative to model development, are given in Table 3N, 3S and 3E. For the 12h data set, the average latitude of storms in the three zones: North, South and Equatorial, is seen to be 25.2N, 16.6N and 10.3N while the

Table 3N. Mean and standard deviation (n mi) of along and across track tropical cyclone displacements (predictands) for specified forecast interval in North-Zone. Also given are average initial position, vector and scalar motion of storms (defined by storm positions at -6h and +6h) and sample size. Positive motion is along or to right of track.

	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
Mean along track displacement.....	126.7	225.7	300.0	355.6	399.4	435.5
Standard deviation of along track displacement.....	89.2	164.4	224.7	277.8	332.0	386.6
Mean across track displacement.....	9.2	28.9	58.6	86.1	95.2	93.2
Standard deviation of across track displacement.....	48.8	114.3	194.3	271.7	340.3	399.8
Average storm location..... (Latitude N and Longitude E)	25.2 137.3	24.5 137.4	24.0 137.6	23.5 137.8	23.1 137.9	22.7 138.0
Initial vector motion..... (deg/s/knots)	011.7/7.4	006.0/6.6	360.0/5.9	354.4/5.5	350.5/5.1	348.4/4.9
Scalar speed (knots).....	10.7	9.7	8.9	8.3	8.0	7.7
Sample size.....	1169	987	830	686	559	449

Table 3S. Mean and standard deviation (n mi) of along and across track tropical cyclone displacements (predictands) for specified forecast interval in South-Zone. Also given are average initial position, vector and scalar motion of storms (defined by storm positions at -6h and +6h) and sample size. Positive motion is along or to right of track.

	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
Mean along track displacement.....	105.9	202.9	290.4	367.3	432.4	488.9
Standard deviation of along track displacement.....	50.6	99.4	149.0	200.3	252.1	304.6
Mean across track displacement.....	6.0	21.9	45.0	80.0	119.9	164.1
Standard deviation of across track displacement.....	30.2	67.6	114.0	171.5	231.4	282.0
Average storm location..... (Latitude N and Longitude E)	16.6 129.4	16.5 130.4	16.3 131.5	16.2 132.7	16.1 133.5	16.0 134.9
Initial vector motion..... (deg/s/knots)	293.0/8.8	293.1/8.8	293.2/8.8	293.3/8.8	293.1/8.8	292.6/8.8
Scalar speed (knots).....	9.4	9.4	9.4	9.4	9.4	9.4
Sample size.....	1063	994	915	835	753	677

Table 3E. Mean and standard deviation (n mi) of meridional and zonal tropical cyclone displacements (predictands) for specified forecast interval in Equatorial-Zone. Also given are average initial position, vector and scalar motion of storms (defined by storm positions at -6h & +6h) and sample size. Positive motion is towards north or east. Negative motion is towards south or west.

	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
Mean meridional displacement.....	41.6	89.1	141.6	197.9	251.4	310.4
Standard deviation of meridional displacement.....	43.2	81.7	119.5	154.4	189.3	226.2
Mean zonal displacement.....	-96.4	-195.4	-290.6	-382.8	-476.4	-564.6
Standard deviation of zonal displacement.....	72.3	139.8	204.1	264.3	315.7	367.5
Average storm location..... (Latitude N and Longitude E)	10.3 140.6	10.3 141.3	10.3 141.7	10.3 142.3	10.2 142.7	10.2 143.0
Initial vector motion..... (deg/s/knots)	292.1/8.6	292.1/8.9	292.0/9.1	292.1/9.2	291.2/9.3	291.0/9.4
Scalar speed (knots).....	10.1	10.3	10.4	10.5	10.6	10.6
Sample size.....	386	365	350	334	319	301

vector motion in the same three zones is seen to be towards 011.7° at 7.4 knots, 293.0° at 8.8 knots and 292.1° at 8.6 knots, respectively. Composite grids for each of the three zones is given in Fig 3. In these Figures, the typhoon symbol is positioned at the average latitude/longitude of storms comprising the given 12h data set. For the North- and South-Zone grids, the storm heading and the along-track grid orientation is towards the vector motion of the collective storms. Operationally, grid alignment is based on average motion over the past 12h rather than the instantaneous initial vector motion as used here but the vector difference in the two quantities is very small. In the Equatorial-Zone, the grid is oriented in a meridional/zonal system and the effective storm motion is towards 360° .

5.2.5 Composite Geopotential Height Fields - The height fields associated with the data sets represented in Table 3 can also be displayed in composite form. For the North- and South-Zones, this is depicted in Fig. 4. Although a similar composite could be accomplished for the Equatorial-Zone, the depiction would not have the same meaning in that grids in that zone are not rotated in accordance with the average motion of the storm over the previous 12h as they are over the North- and South-Zones.

Height patterns depicted in Fig. 4 are typical of those encountered in individual cases with the subtropical anticyclone located to the right-of-track and low heights located left-of-track. It can be noted that there appears to be a small left-of-track bias in the actual (best-track) position of the storm compared to the center suggested by the objective analyses. A similar bias (Figs 7 and 8 of Neumann and McAdie, 1991) exists in the NOAA National Meteorological Center initial analyses used in developing the NHC NHC83 and NHC90 models. Also, the overall height pattern and absolute values of the heights (after allowing for different average latitudes) are remarkably similar to those over the Atlantic basin. This suggests that basic steering patterns associated with storm motion are very similar from one basin to another.

6. PREDICTOR SELECTION

Relevant background and theoretical aspects of geopotential height predictor selection have already been discussed in Section 3.3. Here, the discussion will focus on actual predictors selected for retention in the model using methodology discussed in these earlier Sections. As previously pointed out, geopotential height predictors are required both in Model 2 (Analysis Mode) and in Model 3 (Perfect-Prog Mode) with those in the latter group being averaged over the period of the forecast (Section 3.7).

6.1 CORRELATION AND PARTIAL-CORRELATION FIELDS

The first step in predictor selection was subjective visual examination of the various linear (zero-order), first-, second- and third-order partial correlation fields (Mills, 1953) between component storm motion and the height fields. These four correlation fields are available for each of the six forecast periods, for each of the two components of storm motion, for each of the three stratification zones and for both the Analysis (Model 2) and the Perfect-Prog (Model 3) models. In that this represents 288 fields, only six selected examples from the Perfect-Prog mode will be illustrated here.

Fig. 3. Composite 15 x 11 grid field domains for the three stratification zones, North, South and Equatorial. For each zone, tropical cyclone symbol is positioned at the average position of the n-storms comprising respective 12h data set in that zone (see Tables 3N, 3S and 3E). In addition, grids for the North and South-Zones are rotated according to average (vector) motion of the n-storms in that zone over the period from the 12h-old position of the storm to the initial position. When activating model, actual motion of the storm over that period is used for grid alignment. For the Equatorial-Zone, grid is always rotated with an assumed storm heading of 360°.

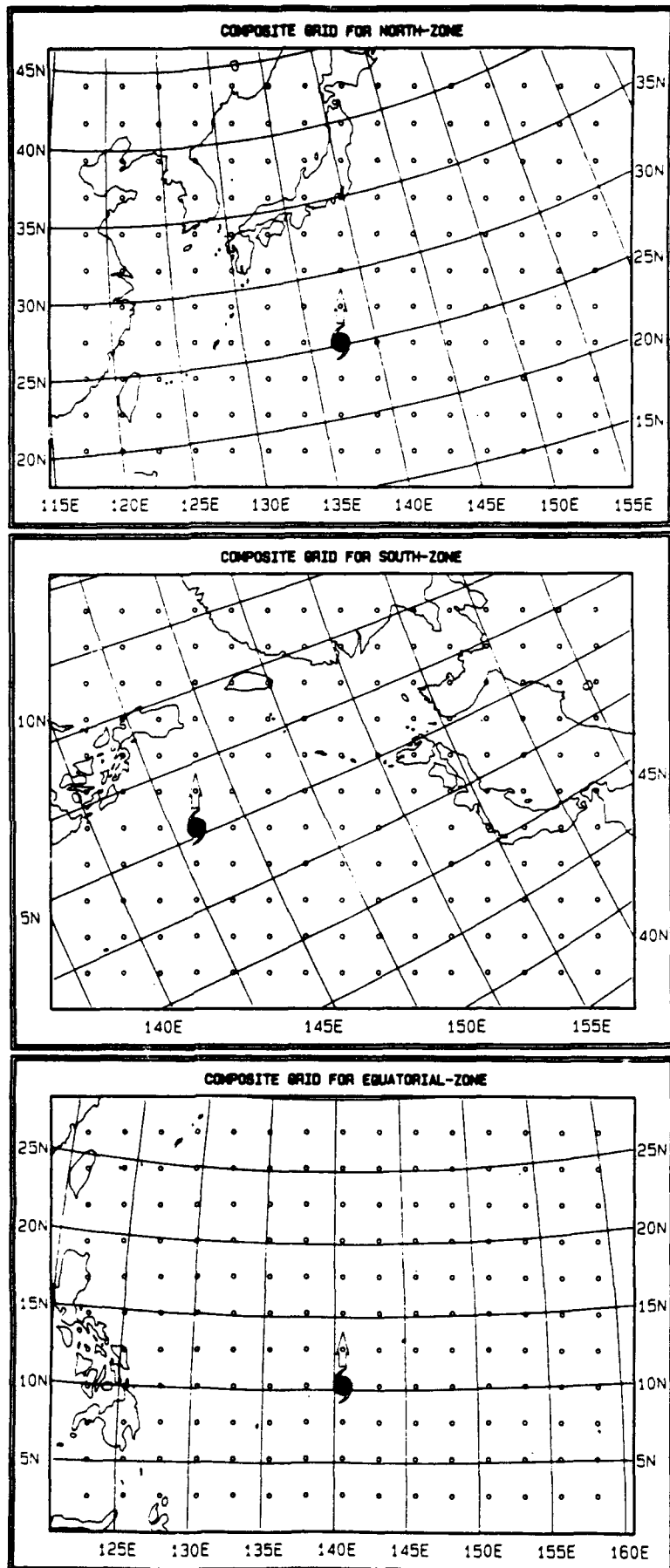
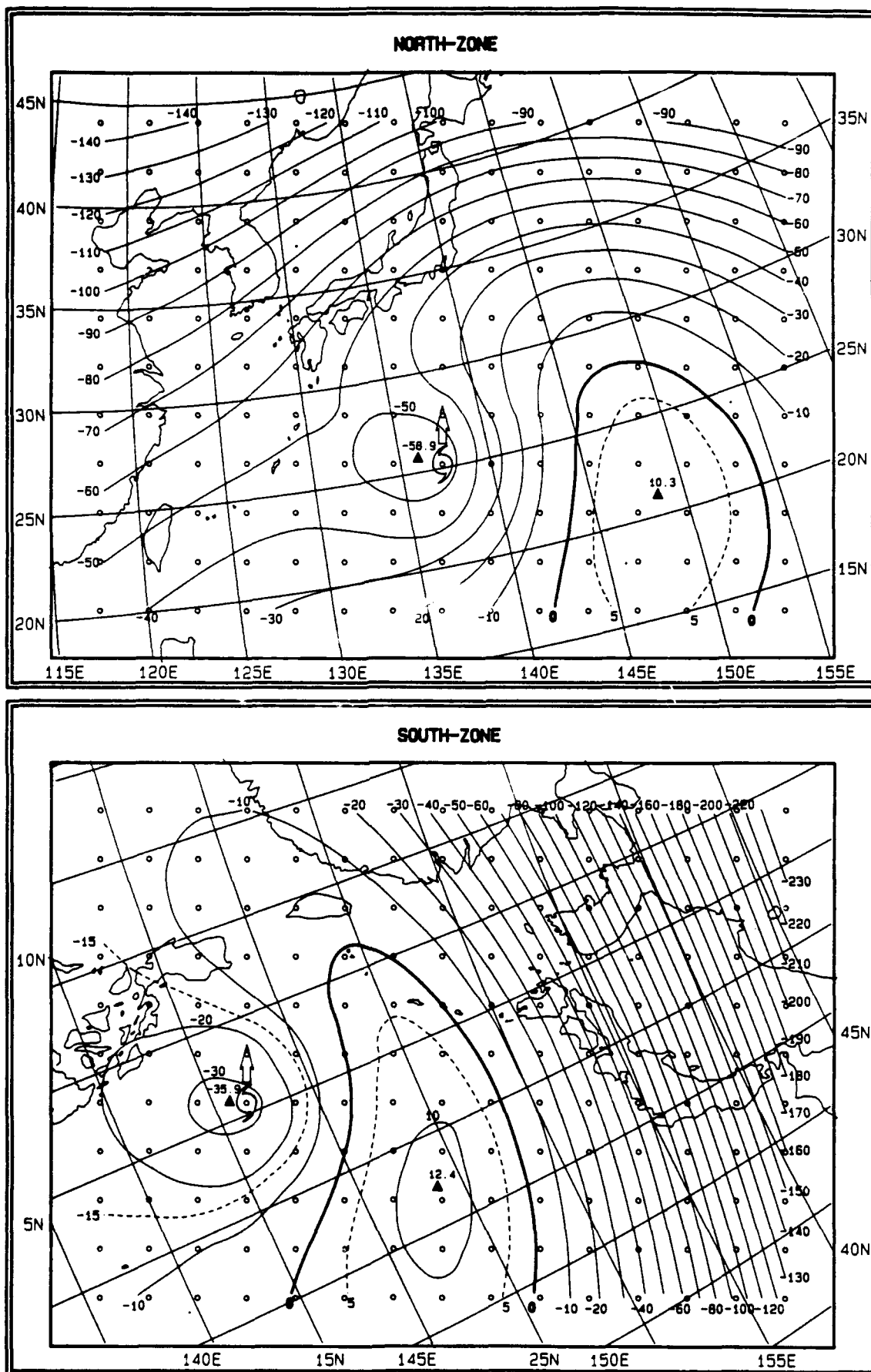


Fig. 4. Composite deep-layer-mean geopotential height fields of developmental data (departure from normal in meters--see Section 3.1) associated with +12h storm motion in the direction indicated by arrow. Shaded triangles show location and value of maxima and minima in the field. Bold contour indicates zero departure from normal.



A study and understanding of these fields assists in the physical interpretation of predictor patterns. Also, they are particularly helpful in determining, along with other objective criteria, which and how many predictors are to be retained in the final model.

In each of these six illustrations (Figs. 5 through 10), depicting selected correlation fields from each of the three zones, actual correlation values between component storm motion and height are available at each of the 165 (15 x 11) grid points. An objective analysis routine was used for the analysis as well as for the location and value of maxima and minima.

6.1.1 Along-Track Motion, Perfect-Prog Mode, North-Zone - Fig. 5 shows the linear (zero-order) correlation field between +12h storm motion and associated geopotential heights. Here, two centers of correlation, one to the left and another to the right of the storm are clearly noted. In that the center to the left of the storm predominates, the predictor closest to the analyzed correlation center (column 5, row 6)⁷ is selected as the best single predictor, i.e., it explains most of the variance (R^2) between storm displacement along the track and geopotential height. It would have been better to select a predictor at the exact analyzed center of correlation, but a grid-point predictor is not available at that location.

Once the above single predictor is selected, the correlation pattern shown in Fig. 5 is no longer valid for selection of additional predictors. Rather, the methodology is to scan the first-order partial correlation field for the second predictor, the second-order partial correlation field for the third predictor, etc. These are the correlation fields that exist given that the previous predictor(s) have already been selected.

The first-order partial correlation field is depicted in Fig. 6. A large star has been positioned at the location of the first selected predictor. As would be expected, the incremental variance reduction from this first predictor is now zero. It can be noted that the center of correlation to the right of the storm is much more vigorous than it was on the zero-order field. Also, the location of the center is considerably different. The physical interpretation here is that, once an initial predictor has been selected, the program, in effect, senses that the two predictors are acting in concert as a "gradient" and a second predictor is selected at column 11, row 8.

In this case, through the generation of second- and third-order partial correlation fields (not shown here), two additional predictors are selected in close proximity to predictors 1 and 2. This occurs in that the location of the first two predictors was not optimal insofar as total variance reduction is concerned. In some cases, forced pairing of predictors (see Section 3.3.2) provides for a more efficient location of these important "steering" predictors. After the selection of a fourth predictor, further incremental variance reduction is not significant in the statistical sense using the strict criteria discussed in Section 3.3.1.

For the Atlantic basin, Neumann (1988b), in his Figs. 6 and 7, shows comparable correlation fields to those given in our Figs. 5 and 6. The corre-

⁷The top, left-hand corner is taken as column 1, row 1.

Fig. 5. Linear (zero-order) correlation coefficient between 12h along-track motion (positive) and deep-layer-mean geopotential heights in the North-Zone and for Perfect-Prog mode. Storm is located at average position and is moving towards resultant motion of the 1169 storms comprising the developmental data set. Contour labels are in units of correlation coefficient $\times 100$. Bold line indicates zero correlation. Dark triangles (\blacktriangle) show location of specified maxima and minima in field.

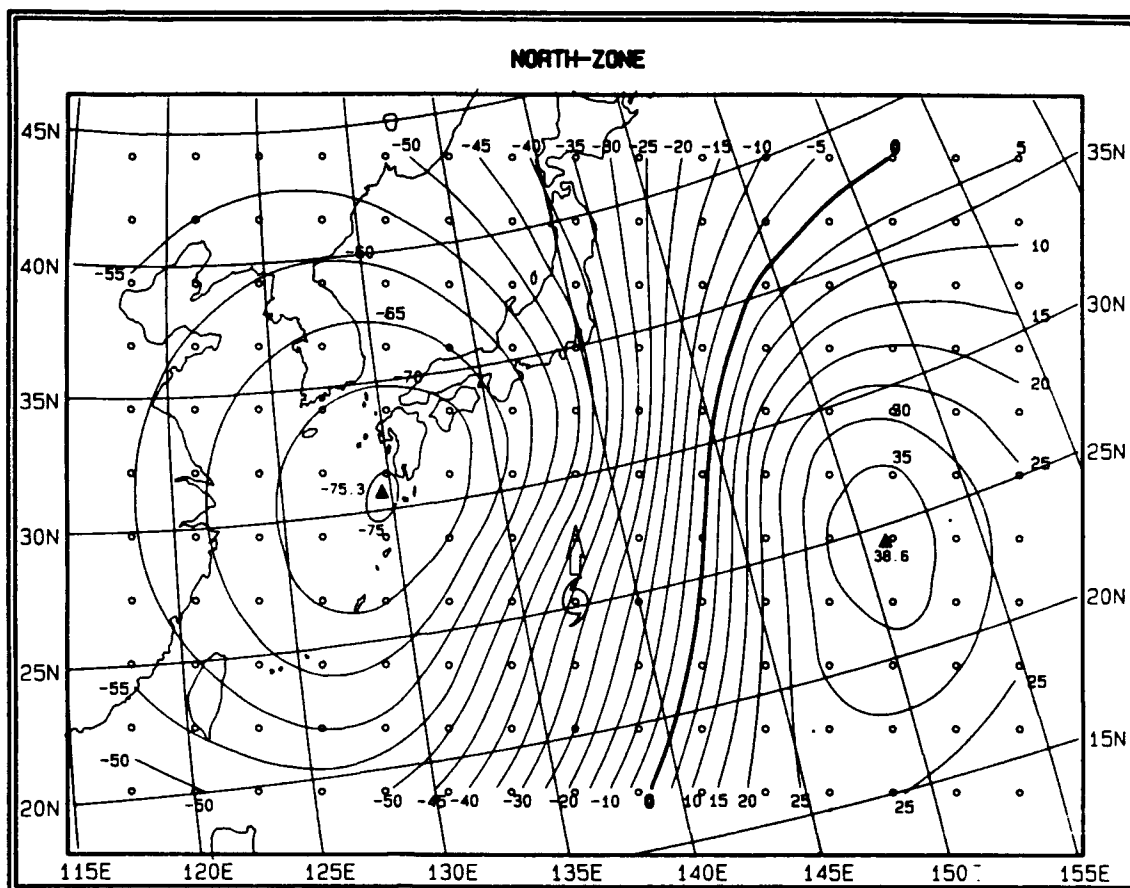


Fig. 6. Same as Fig. 5 except for first-order partial correlation fields. Star (\star) gives location of predictor selected in previous step.

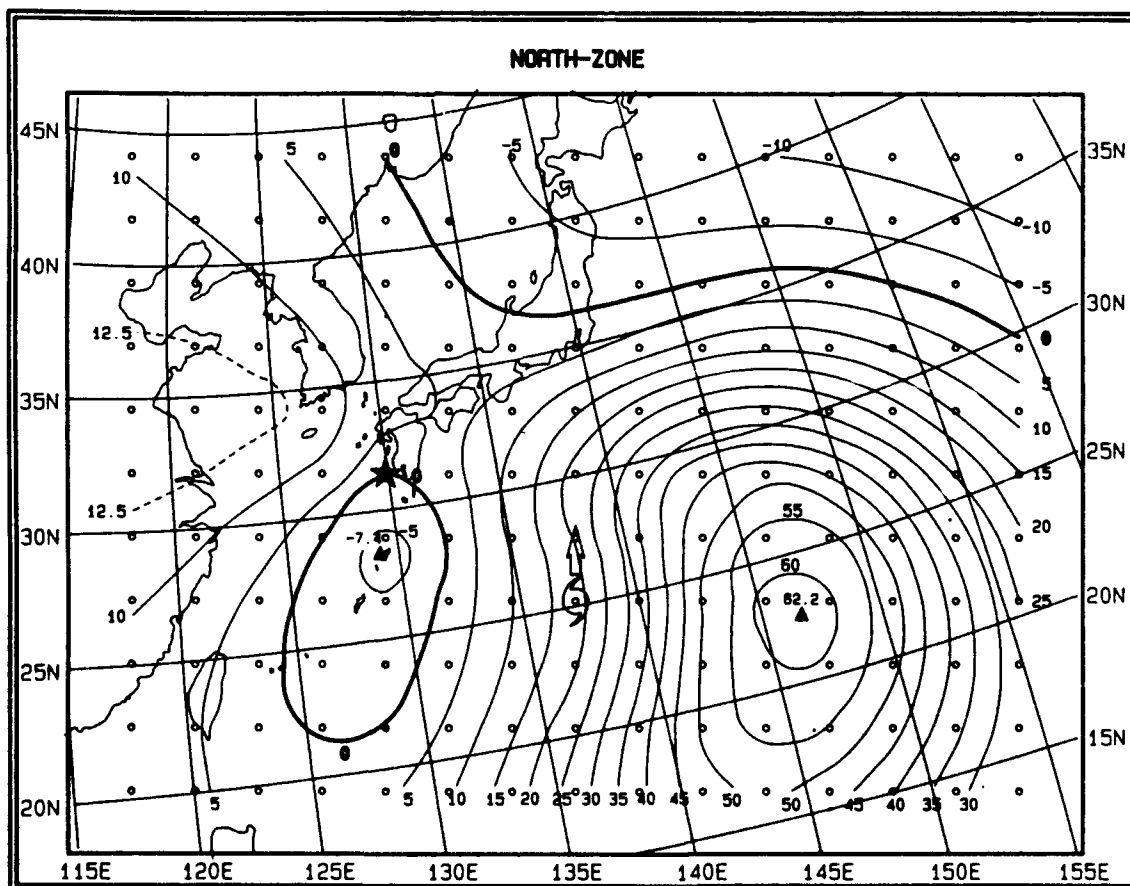


Fig. 7. Linear (zero-order) correlation coefficient between 72h across-track motion (motion to right is positive) and deep-layer-mean geopotential heights in the North-Zone and for Perfect-Prog mode. Storm is located at average position and is moving towards resultant motion of the 449 storms comprising the developmental data set. Contour labels are in units of correlation coefficient $\times 100$. Bold line indicates zero correlation. Dark triangles (\blacktriangle) show location of specified maxima and minima in field.

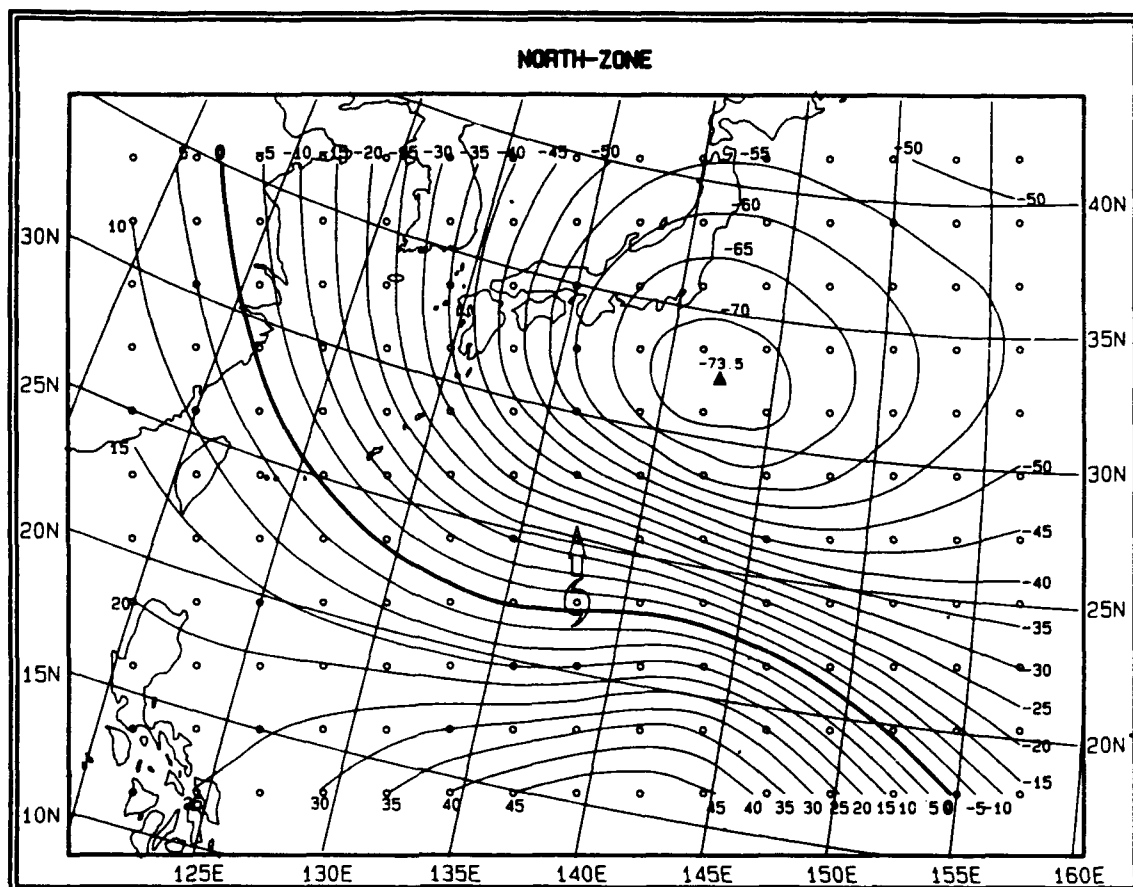
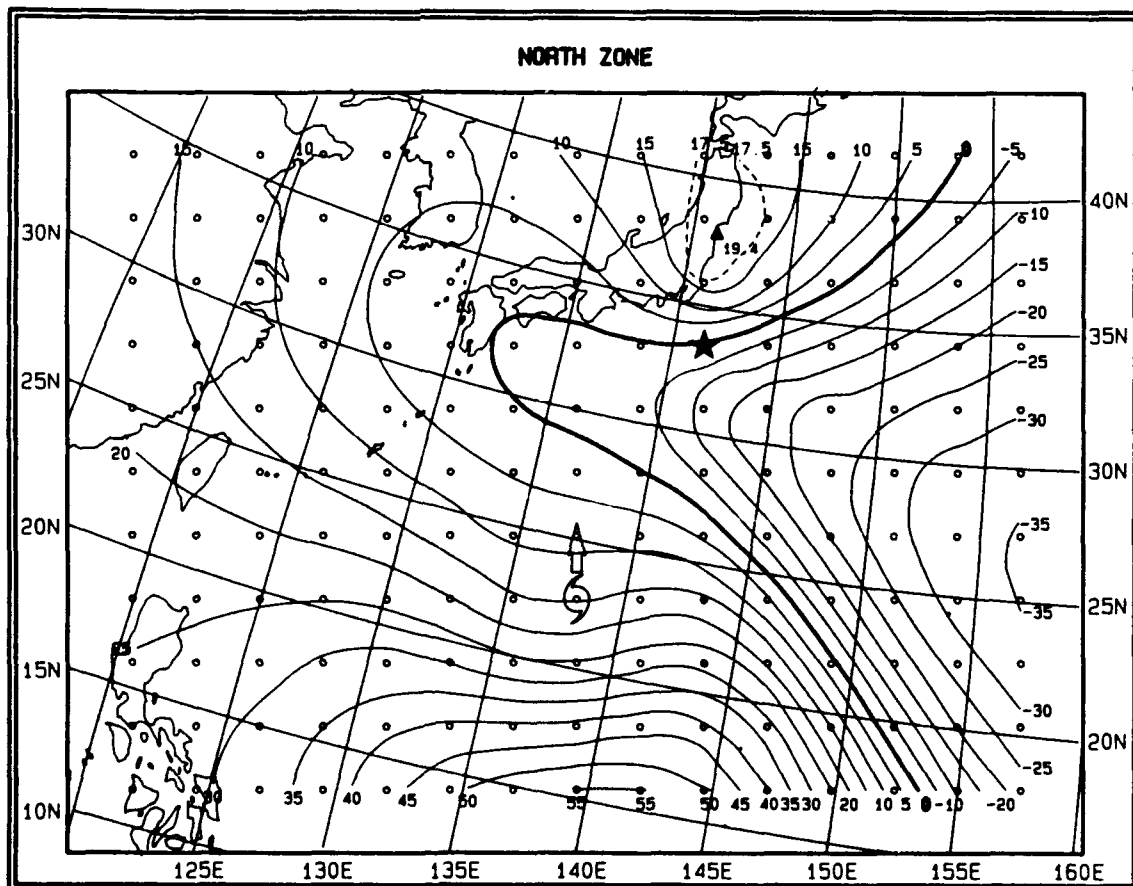


Fig. 8. Same as Fig. 7 except for first-order partial correlation fields. Star (\star) gives location of predictor selected in previous step.



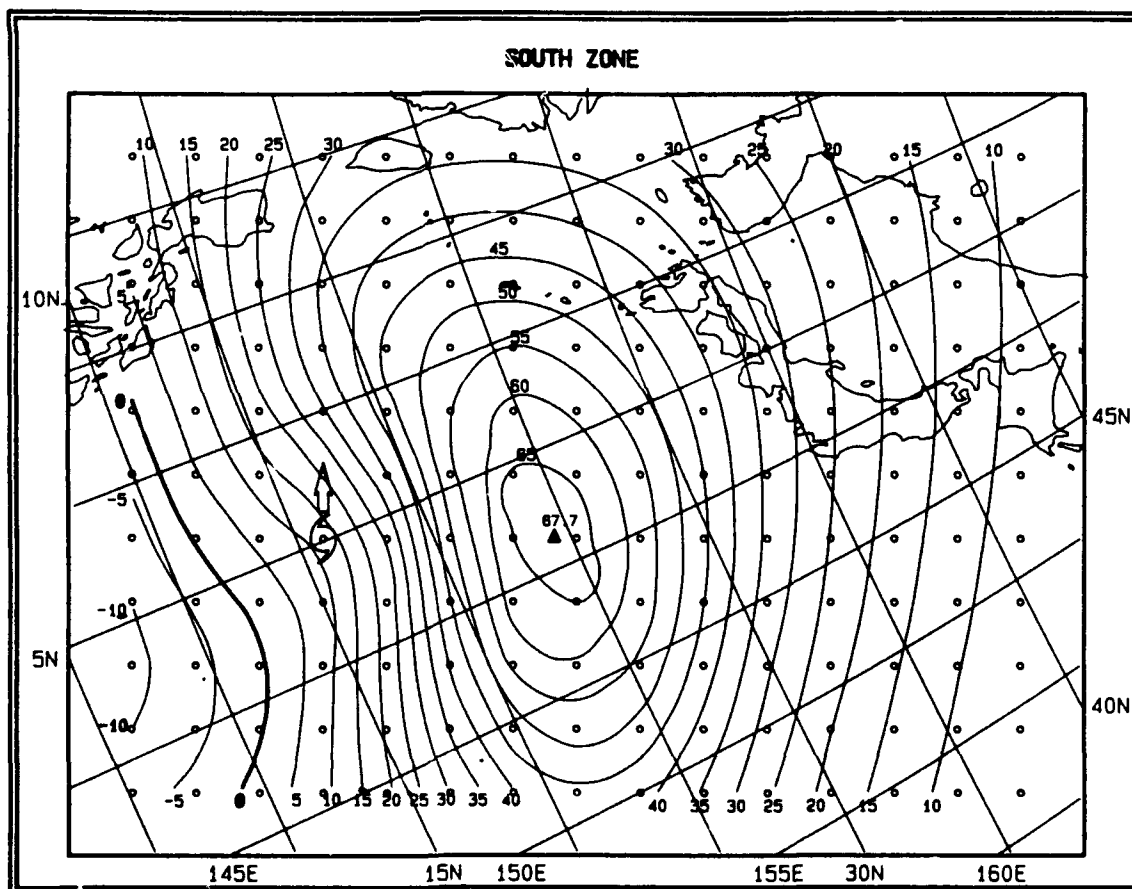
lation patterns, the position of maxima and minima as well as the values of maxima and minima are remarkably similar between the two basins. This is even more remarkable in that different analysis methodology and different periods of record are involved here. This suggests that these predictors are extremely "robust" insofar as motion prediction is concerned. It further suggests that similar environmental forces are manifest in both basins.

6.1.2 Across-Track Motion, Perfect-Prog Mode, North-Zone - Figs. 7 and 8 show the zero-and first-order partial correlation fields for 72h across-track motion in the North-Zone. These can be compared to Figs. 6 and 7 of Neumann (1988b). Again, the patterns here are quite similar between basins although the similarity is not as striking as it was in the case of 12h along-track motion, discussed in Section 6.1.

Here, as with other height predictors, it can be noted that the location of predictors is rather distant from the storm such that they cannot be considered as mere "steering" predictors. Rather, they should be considered as "implied steering" predictors in that the steering is suggested by the larger-scale synoptic pattern.

In Fig. 8, the maximum correlation at the bottom of the Chart led to the selection of the second predictor at column 9, row 11. The circumstance that this location is at the lower bound of the grid suggests that grid points with higher correlation could be positioned outside the grid domain. However, moving the grid farther to the south showed that this did not occur.

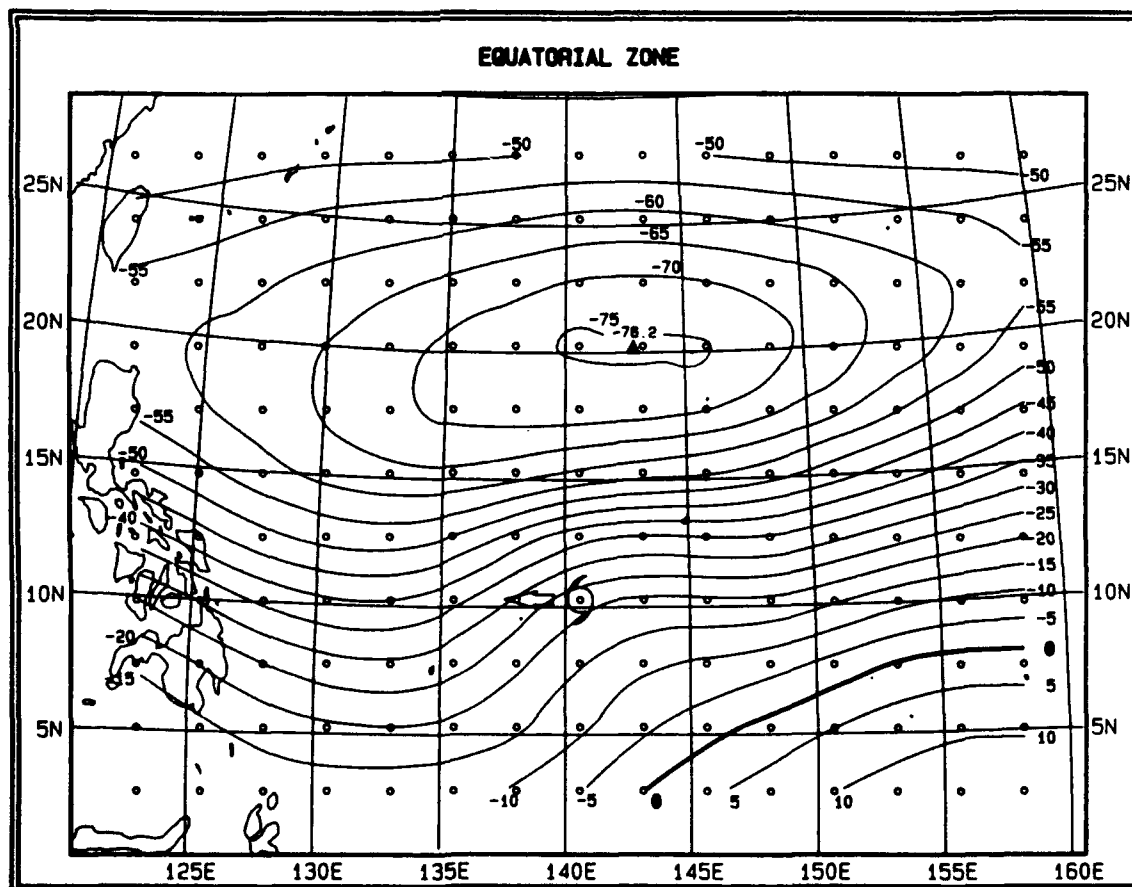
Fig. 9. Linear (zero-order) correlation coefficient between 72h along-track motion (positive) and deep-layer mean geopotential heights in the South-Zone and for Perfect-Prog mode. Storm is located at average position and is moving towards resultant motion of the 677 storms comprising the developmental data set. Contour labels are in units of correlation coefficient x 100. Bold line indicates zero correlation. Dark triangle (\blacktriangle) shows location of specified maxima and minima in field.



6.1.3 Along-Track Motion, Perfect-Prog Mode, South-Zone - Turning now to storms located in the South-Zone, Fig. 9 shows the linear (zero-order) correlation coefficient field between 72h along-track motion and the geopotential heights over the grid-domain. Here, in contrast to Fig. 5, maximum correlation is located to the right, rather than to the left of the storm. Indeed, correlations on the equatorward side of the storm are too close to zero to be significant. Thus, in the statistical sense, motion of storms in this zone is controlled primarily by the location and intensity of the subtropical anticyclone whereas in the North-Zone, the location and intensity of perturbations in the westerlies (upstream from the storm) were more important in controlling storm motion. This is an important reason for separating storms in the easterlies from those in the westerlies as was done here.

6.1.4 Along-Track Motion, Perfect-Prog Mode, Equatorial-Zone - One final illustration of correlation patterns (Fig. 10) is for the Equatorial-Zone. Here, it should be recalled, the grid is not rotated in accordance with initial storm motion; rather, it is positioned in the traditional meridional/zonal sense (see Section 5.2.2) with meridional motion being equivalent to along-track motion and zonal motion being equivalent to across-track motion. Here it can be noted that zonal motion is controlled primarily by the position and intensity of the subtropical ridge line, with maximum correlation positioned some 600 n mi (1112 km) poleward from the storm.

Fig. 10. Linear (zero-order) correlation coefficient ($\times 100$) between 72h zonal motion (motion towards west is negative) and deep-layer-mean geopotential heights in the Equatorial-Zone and for Perfect-Prog mode. Storm is located at average position of the 301 storms comprising the developmental data set. Bold line indicates zero correlation. Dark triangle (\blacktriangle) shows location of specified maxima and minima in field.



6.2 FINAL LOCATION OF PREDICTORS

Final predictor selection was governed both by subjective and by objective considerations. Initially, correlation fields, a few of which were illustrated in the previous Section, were examined. Next, these fields were reexamined using the "forced-pairing" methodology discussed in Section 3.3.2. If the latter produced a more efficient set of predictors (i.e., same or greater variance reduction with fewer predictors), it was used. However, as further discussed in Section 3.3.2, forced-pairing was not used if the methodology resulted in predictors being positioned too close to the storm. A final consideration was the desire to maintain consistency in predictor selection (see Section 3.3.3).

Figs. 11, 12 and 13, for both the Analysis and the Perfect-Prog mode, show the final predictor locations for each of the three stratification zones. Depending on considerations noted in the preceding paragraph, these positions may or may not coincide with those in the final predictor layout given in Figs. 5 through 10. It can be noted that the minimum number of geopotential height predictors in a given unit was two and the maximum was four.

7. STRUCTURING OF FINAL MODEL

7.1 COMBINING MODELS

As previously discussed, the final model (Model 5) is based on contributions from Model 1 (predictors from climatology and persistence), Model 2, (geopotential height predictors from initial analysis only) and Model 3 (geopotential height predictors from Perfect-Prog fields through 72h). Each of these models produces a forecast of component storm displacements through the 72h projection. To arrive at a final (Model 5) forecast, these displacements are combined using regression coefficients determined from the developmental data set. Symbolically, for a given zone and given forecast interval,

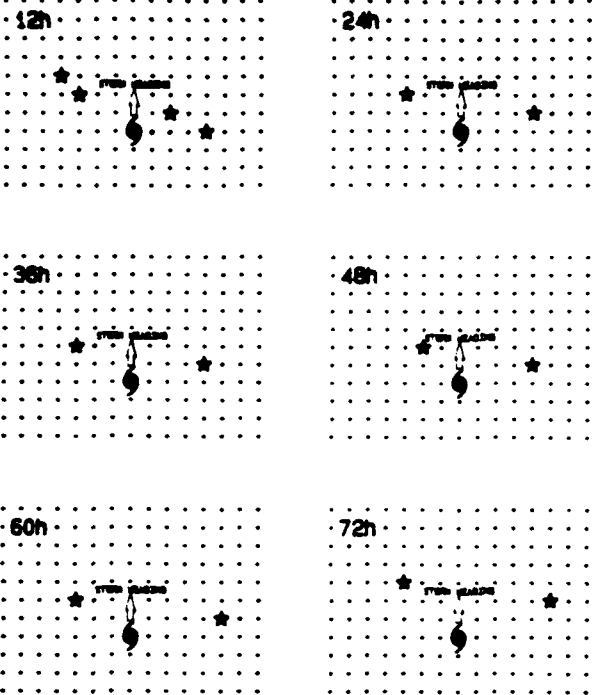
$$D_5 = C_0 + C_1 D_1 + C_2 D_2 + C_3 D_3, \quad (2)$$

where D_5 is the final Model 5 displacement for the given zone and forecast interval, C_0 is the intercept value, $C_1 D_1$, $C_2 D_2$ and $C_3 D_3$ are regression coefficients and previously determined forecast displacements for Model 1, Model 2 and Model 3, respectively. Examination of regression coefficients shows substantial differences in the weighting of the Models 1, 2 and 3, depending on zone and forecast interval. As would be expected, model 1 contributions are highest for the short range projections, whereas Model 3 contributions are highest for the extended projections. Also, Model 1 weighting tends to be higher in the South and the Equatorial Zone.

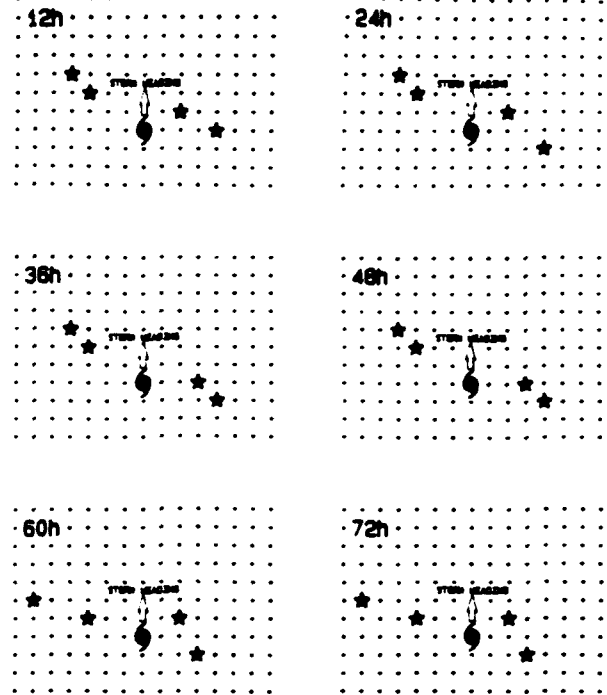
7.2 PERFORMANCE ON DEVELOPMENTAL DATA

7.2.1 Total Variance Reduction - For Model 1 (Climatology and Persistence), Model 2 (Analysis mode) and Model 3 (Perfect Mode), Tables 4, 5, and 6, respectively, give total variance reduction between tropical cyclone motion and the ensemble of predictors in each Model. In each of the three tables, it can be noted that variance reduction is higher in the case of along-track motion

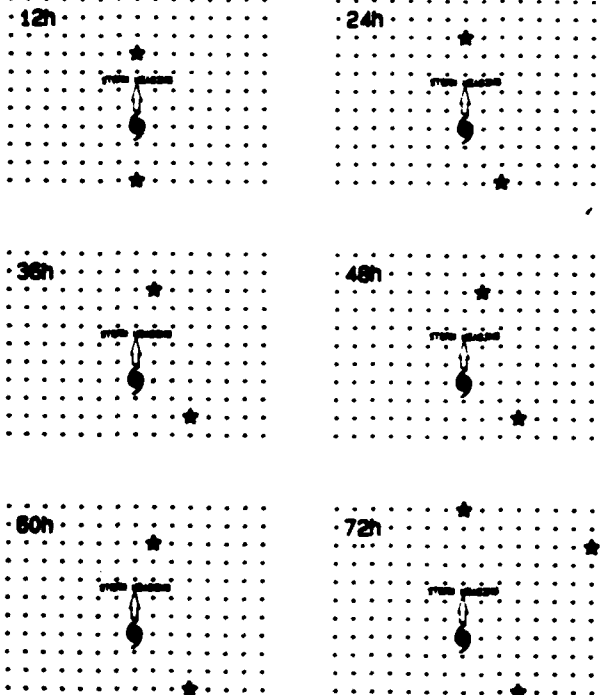
ALONG TRACK MOTION, ANALYSIS MODE, NORTH-ZONE



ALONG TRACK MOTION, PERFECT-PROG MODE, NORTH-ZONE



ACROSS TRACK MOTION, ANALYSIS MODE, NORTH-ZONE



ACROSS TRACK MOTION, PERFECT-PROG MODE, NORTH-ZONE

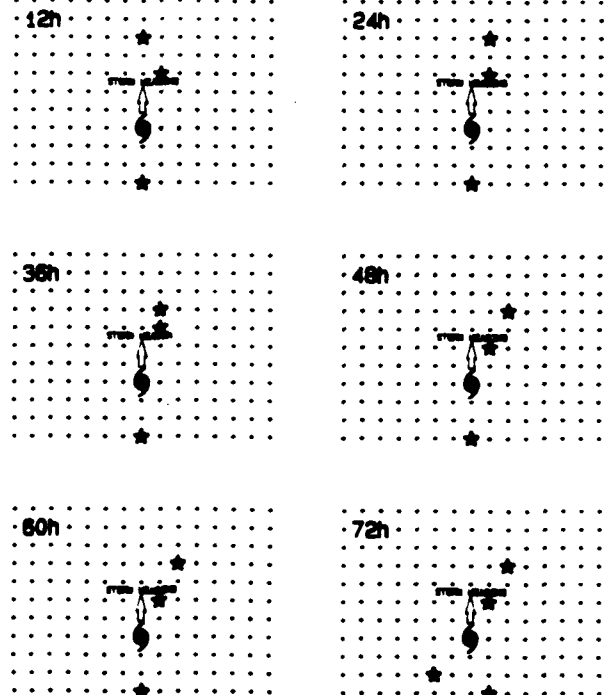
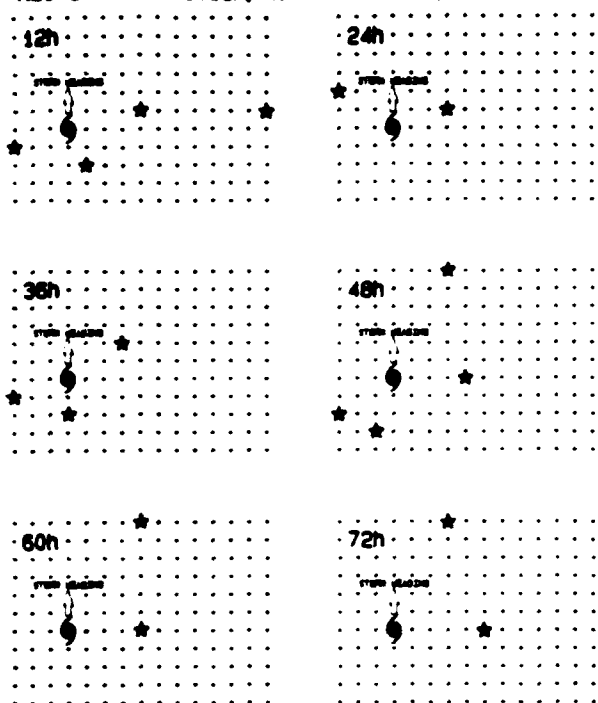
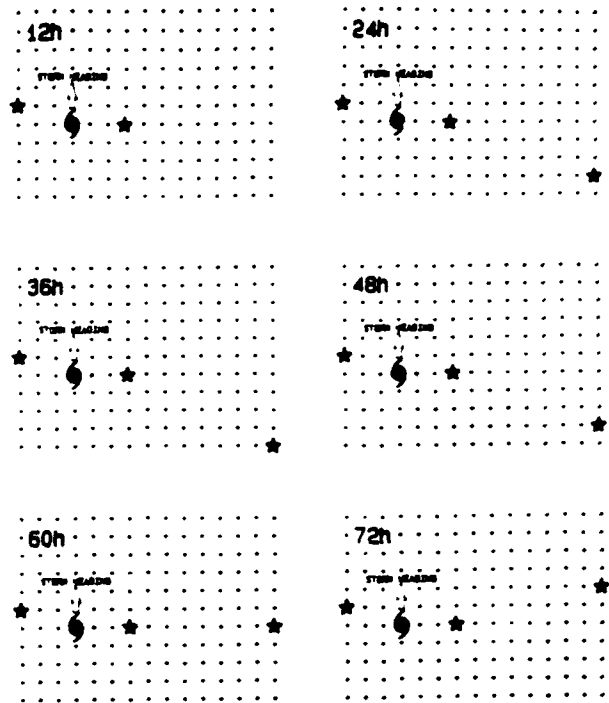


Fig. 11. 15 x 11 grid-layout and geopotential height predictor locations (starred grid-points) for the North-Zone. Perfect-Prog predictor values are averaged over forecast period (see Section 3.7).

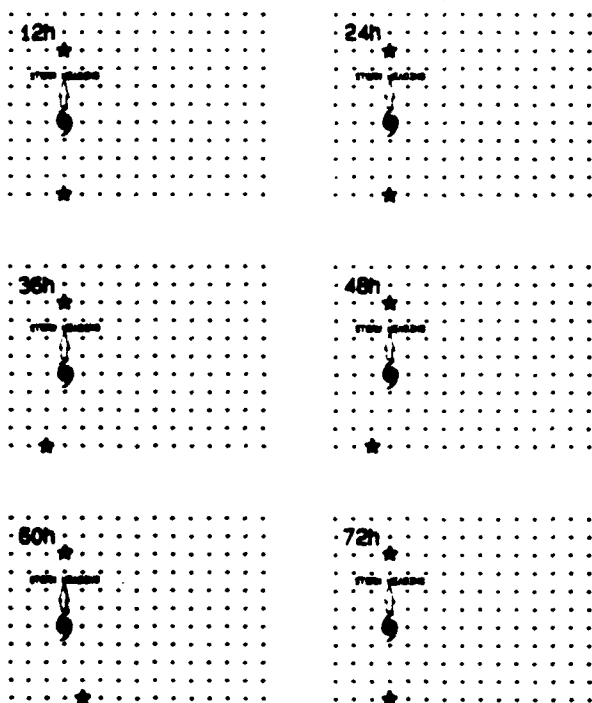
ALONG TRACK MOTION, ANALYSIS MODE, SOUTH-ZONE



ALONG TRACK MOTION, PERFECT-PROG MODE, SOUTH-ZONE



ACROSS TRACK MOTION, ANALYSIS MODE, SOUTH-ZONE



ACROSS TRACK MOTION, PERFECT-PROG MODE, SOUTH-ZONE

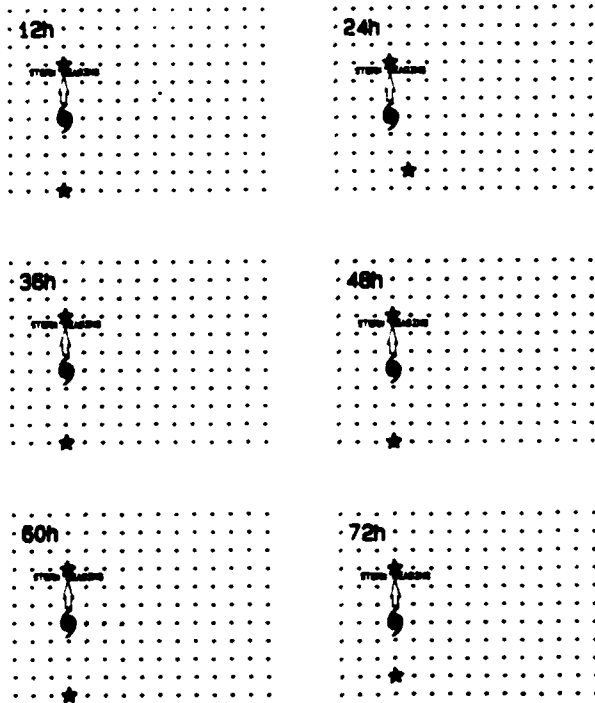
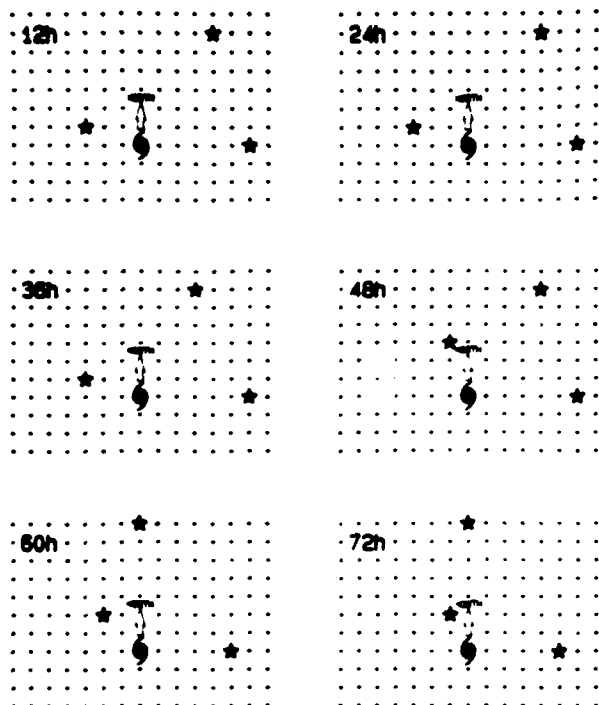
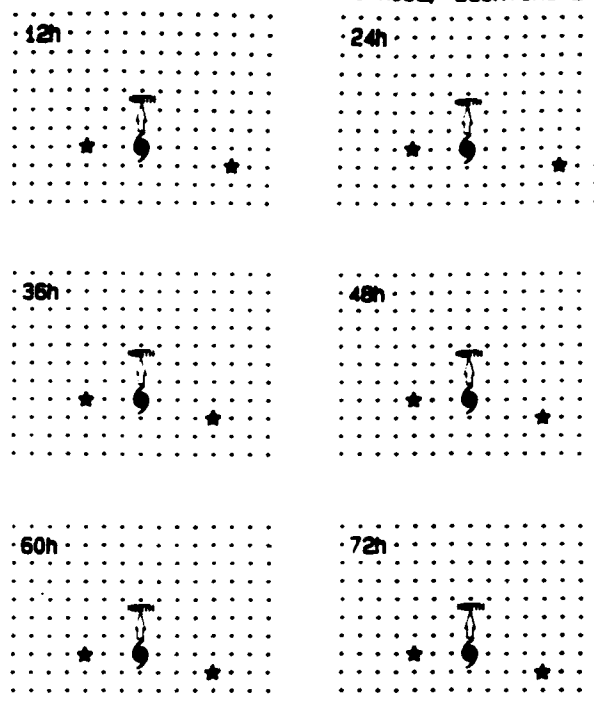


Fig. 12. 15 x 11 grid-layout and geopotential height predictor locations (starred gridpoints) for the South-Zone. Perfect-Prog predictor values are averaged over forecast period (see Section 3.7).

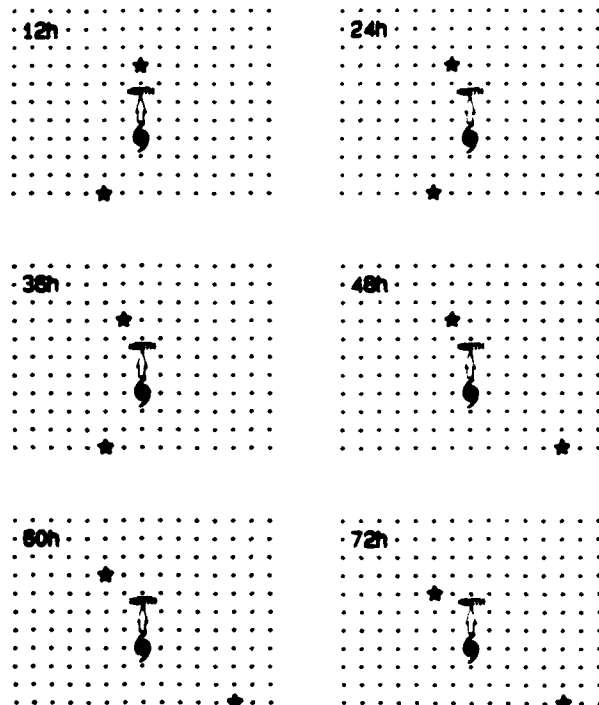
MERIDIONAL MOTION, ANALYSIS MODE, EQUATORIAL-ZONE



MERIDIONAL MOTION, PERFECT-PROG MODE, EQUATORIAL-ZONE



ZONAL MOTION, ANALYSIS MODE, EQUATORIAL-ZONE



ZONAL MOTION, PERFECT-PROG MODE, EQUATORIAL-ZONE

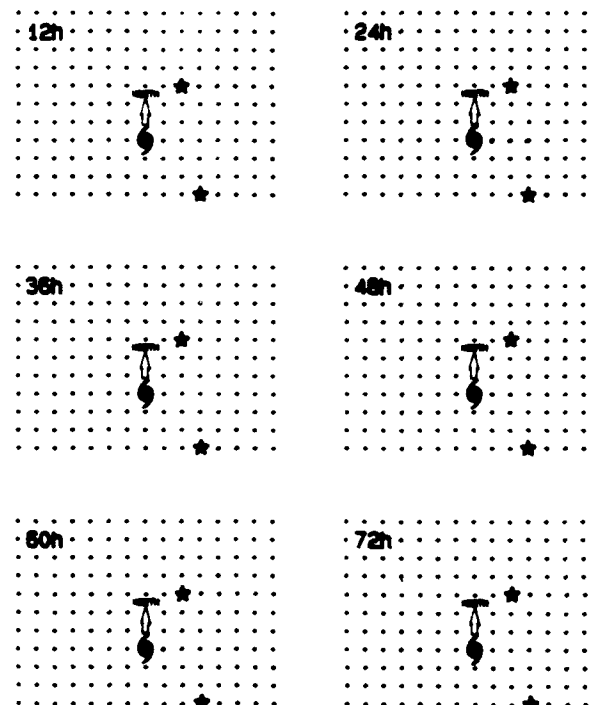


Fig. 13. 15 x 11 grid-layout and geopotential height predictor locations (starred gridpoints) for the Equatorial-Zone. Perfect-Prog predictor values are averaged over forecast period (see Section 3.7).

in the North- and South-Zones and for equivalent zonal motion in the Equatorial-Zone. This is not due to better model performance for this component of motion. Rather, it is due to the combined effect of both higher standard errors⁸ and higher standard deviations (see Table 3) of storm motion within these zones. Reduction of variance (R^2) is a function both of standard error (S_e) and the standard deviation (S_d),

$$R^2 = 1 - S_e^2 / S_d^2. \quad (3)$$

Although standard errors are not included in this document, they could be computed from a transposition of (3). For example, consider 12h Model 1 (CLIPER) errors for North-Zone along-track motion. From Table 3N, standard deviation is seen to be 89.2 n mi while from Table 4, reduction of variance is seen to be 0.892. This yields a standard error of 29.3 n mi. Similarly, it can be shown that for across-track motion, given the same Model, Zone and 12h projection, the standard error is 33.3 n mi.

In Tables 4, 5 and 6, it can also be noted that, for Model 1 and Model 2, the variance reduction decreases with increased forecast interval whereas for Model 3, variance reduction increases or remains constant with increased forecast interval. This is an artifact of the Perfect-Prog methodology as well as conditions of Eq. (3).

With one exception, variance reductions from the Perfect-Prog Mode model, are greater than for the Analysis Mode model and it can be further noted that these differences increase with forecast interval. The one exception occurs in the case of 12h reductions in the South-Zone for along-track motion where the reduction from the Analysis mode (0.637) is slightly greater than for the Perfect-Prog mode (0.623). Considering the rationale of the model where the Perfect-Prog model additionally uses 12h analysis fields, this seems contradictory. However, the explanation lies in the retention of additional predictors (see Fig. 12) for the Analysis mode. Thus, the increased variance reduction for the Analysis mode is an artifact of the predictor retention process.

Table 7 gives the total variance reduction for the final Model 5. Here, as would be expected, the reduction, for any given component of motion and zone, is higher than for any of the three component Models 1, 2 and 3.

7.2.2 Forecast Errors - Tables 8, 9 and 10, for the North-, South- and Equatorial-Zones, respectively, give the total forecast error for the respective models. As would be expected, errors from Model 3, are less than for Models 1 and 2, with the differences increasing with increased projection. One exception to this occurs in comparing 12h Model 2 error for the South-Zone (41.0 n mi) to that of Model 3 (41.3 n mi). This is related to the predictor selection artifact noted in the previous section.

It can also be noted that Model 1 (CLIPER) errors are less for some of the early projections. This occurs in that best-track CLIPER errors are

⁸Standard error is the standard deviation of component errors (residuals) about the regression line, plane or hyperplane.

Table 4. Developmental data [Model 1 (CLIPER mode)] reduction of variance ($0 \leq R^2 \leq 1$) of tropical cyclone motion for specified forecast interval and for specified zone and component of motion.

	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
North Zone along track						
variance reduction.....	0.892	0.818	0.725	0.673	0.615	0.568
North Zone across track						
variance reduction.....	0.533	0.618	0.644	0.627	0.619	0.581
Sample size.....	1169	987	830	686	559	449
South Zone along track						
variance reduction.....	0.832	0.782	0.733	0.693	0.664	0.639
South Zone across track						
variance reduction.....	0.320	0.371	0.385	0.405	0.383	0.363
Sample size.....	1063	994	915	835	753	677
Equatorial Zone meridional						
variance reduction.....	0.757	0.665	0.599	0.559	0.533	0.512
Equatorial Zone zonal						
variance reduction.....	0.893	0.859	0.821	0.782	0.738	0.701
Sample size.....	386	365	350	334	319	301

Table 5. Developmental data [Model 2 (analysis mode)] reduction of variance ($0 \leq R^2 \leq 1$) of tropical cyclone motion for specified forecast interval and for specified zone and component of motion. Sample size same as given in Table 4.

	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
North Zone along track						
variance reduction.....	0.858	0.784	0.703	0.610	0.520	0.424
North Zone across track						
variance reduction.....	0.591	0.625	0.608	0.564	0.516	0.525
South Zone along track						
variance reduction.....	0.637	0.604	0.603	0.605	0.494	0.442
South Zone across track						
variance reduction.....	0.327	0.355	0.366	0.338	0.277	0.229
Equatorial Zone meridional						
variance reduction.....	0.477	0.531	0.553	0.544	0.589	0.615
Equatorial Zone zonal						
variance reduction.....	0.721	0.722	0.726	0.695	0.623	0.573

Table 6. Developmental data [Model 3 (Perfect-Prog mode)] reduction of variance ($0 \leq R^2 \leq 1$) of tropical cyclone motion for specified forecast interval and for specified zone and component of motion. Sample size same as given in Table 4.

	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
North Zone along track						
variance reduction.....	0.884	0.889	0.889	0.889	0.905	0.915
North Zone across track						
variance reduction.....	0.676	0.796	0.859	0.884	0.902	0.914
South Zone along track						
variance reduction.....	0.623	0.688	0.725	0.760	0.788	0.798
South Zone across track						
variance reduction.....	0.404	0.560	0.685	0.774	0.809	0.831
Equatorial Zone meridional						
variance reduction.....	0.489	0.555	0.608	0.638	0.687	0.732
Equatorial Zone zonal						
variance reduction.....	0.744	0.784	0.813	0.839	0.837	0.838

Table 7. Developmental data reduction of variance ($0 \leq R^2 \leq 1$) of tropical cyclone motion obtained by combining above three models (Models 1, 2 and 3) into a single model (Model 5...see Fig. 6). Sample size is identical to that given in Table 4.

	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
North Zone along track variance reduction.....	0.932	0.911	0.900	0.896	0.909	0.919
North Zone across track variance reduction.....	0.709	0.820	0.875	0.892	0.907	0.919
South Zone along track variance reduction.....	0.855	0.850	0.838	0.840	0.850	0.855
South Zone across track variance reduction.....	0.461	0.615	0.724	0.799	0.829	0.840
Equatorial Zone meridional variance reduction.....	0.779	0.737	0.729	0.741	0.773	0.817
Equatorial Zone zonal variance reduction.....	0.909	0.894	0.887	0.893	0.892	0.892

always artificially low for the short-range projections. In an operational mode, the present, -12h and -24h storm positions are not known with the same precision as implied by the best-track.

Finally, Table 11 gives the developmental data forecast errors for the entire model. These data were obtained by combining the errors from the previous three tables, weighted by sample size. Here, as would be expected, the forecast errors from the final Model 5 are considerably less than for the other models. Also included in Table 11, is the percentage reduction of Model 5 errors over those obtained from only the CLIPER (Model 1) errors.

These data can be compared to those given in Neumann's (1988b) Table 10 for the Atlantic NHC83 model where errors, 12 through 72h are given as 25.2, 62.6, 103.5, 134.3, 168.8 and 194.3 for 12 through 72h with a sample size of 1028, 891, 769, 658, 564 and 481 cases. It can be noted that NHC83 errors are less for the short-range projections and greater for the extended projections with the cross-over point estimated to be near 42h. Indeed, the 12h errors (25.2 n mi) for the Atlantic are much less than the 35.4 n mi for the Western Pacific for that same forecast interval. This raises the question as to why the differences. The question is particularly appropriate in that it was pointed out in Section 6.1.1 that the Perfect-Prog correlation fields were remarkably similar between the two basins.

The explanation is related to different ways of structuring the CLIPER model between the two basins. In the Atlantic, initial best-track CLIPER motion (Neumann, 1972) is derived from storm motion between the +6h and -6h whereas in the WPCLPR model (Neumann, 1992) it is derived from the current storm position and the 12h old position. Thus, in the best-track mode, The Atlantic CLIPER model has a 6h advantage over the WESPAC model. In that CLIPER (Model 1) is one of the three models from which Model 5 is derived, CLIPER is much more heavily weighted in Eq. (2) for the Atlantic than it is for the Pacific. The CLIPER weighting in the JTC92 model is probably much more realistic than it is in the Atlantic NHC83 model.

Table 8. Developmental (dependent data) forecast errors (n mi) for North Zone storms for Model 1 (CLIPER), Model 2 (Analysis mode) and Model 3 (Perfect-Prog mode). Also given are forecast errors from Model 4 (CLIPER & Analysis) and Model 5 (CLIPER, Analysis and Perfect-Prog).

<u>Errors from:</u>	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
MODEL 1 (CLIPER).....	47.0	108.1	179.7	250.6	320.3	389.9
MODEL 2 (ANALYSIS).....	51.0	115.3	188.4	267.5	349.4	421.9
MODEL 3 (PERFECT-PROG).....	46.5	87.3	122.8	154.6	176.0	194.7
MODEL 4 (Models 1 and 2 combined)	43.0	100.2	169.6	239.0	310.2	383.4
MODEL 5 (Models 1, 2 and 3 combined)	39.3	79.5	116.3	149.5	172.5	190.7
Percentage improvement of Model 5 over Model 1.....	16.4	26.4	35.3	40.3	46.1	51.1
Sample size.....	1169	987	830	686	559	449

Table 9. Developmental (dependent data) forecast errors (n mi) on South Zone storms for Model 1 (CLIPER), Model 2 (Analysis mode) and Model 3 (Perfect-Prog mode). Also given are forecast errors from Model 4 (CLIPER & Analysis) and Model 5 (CLIPER, Analysis and Perfect-Prog).

<u>Errors from:</u>	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
MODEL 1 (CLIPER).....	33.5	75.5	125.5	181.6	241.5	299.0
MODEL 2 (ANALYSIS).....	41.0	87.6	138.1	192.1	266.8	330.4
MODEL 3 (PERFECT-PROG).....	41.3	78.3	113.7	145.9	178.3	205.4
MODEL 4 (Models 1 and 2 combined)	32.1	72.1	119.4	172.1	234.8	292.6
MODEL 5 (Models 1, 2 and 3 combined)	31.5	63.6	98.0	129.2	160.0	187.3
Percentage improvement of Model 5 over Model 1.....	6.0	15.8	21.9	28.9	33.7	37.3
Sample size.....	1063	994	915	835	753	677

Table 10. Developmental (dependent data) forecast errors (n mi) on Equatorial Zone storms for Model 1 (CLIPER), Model 2 (Analysis mode) and Model 3 (Perfect-Prog mode). Also given are forecast errors from Model 4 (CLIPER & Analysis) and Model 5 (CLIPER, Analysis and Perfect-Prog).

<u>Errors from:</u>	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
MODEL 1 (CLIPER).....	36.7	81.7	132.6	182.5	230.5	277.5
MODEL 2 (ANALYSIS).....	54.3	102.4	149.2	199.4	251.5	299.9
MODEL 3 (PERFECT-PROG).....	52.9	96.2	132.8	164.2	195.2	223.2
MODEL 4 (Models 1 and 2 combined)	35.0	76.0	120.7	167.9	214.2	256.0
MODEL 5 (Models 1, 2 and 3 combined)	34.3	71.7	108.7	137.6	164.2	187.8
Percentage improvement of Model 5 over Model 1.....	6.5	12.2	18.0	24.6	28.8	32.4
Sample size.....	386	365	350	334	319	301

Table 11. Developmental (dependent data) forecast errors (n mi) on North, South and Equatorial Zones combined for Model 1 (CLIPER), Model 2 (Analysis mode) and Model 3 (Perfect-Prog mode). Also given are forecast errors from Model 4 (CLIPER & Analysis) and Model 5 (CLIPER, Analysis & Perfect-Prog).

<u>Errors from:</u>	<u>12h</u>	<u>24h</u>	<u>36h</u>	<u>48h</u>	<u>60h</u>	<u>72h</u>
MODEL 1 (CLIPER).....	40.0	90.2	148.2	207.3	266.4	323.1
MODEL 2 (ANALYSIS).....	47.4	101.6	159.9	221.3	292.1	352.8
MODEL 3 (PERFECT-PROG).....	45.3	84.9	120.5	152.4	180.3	205.8
MODEL 4 (Models 1 and 2 combined)	37.4	84.5	139.5	196.1	256.6	313.4
MODEL 5 (Models 1, 2 and 3 combined)	35.4	71.5	107.0	138.2	165.1	188.5
Percentage improvement of Model 5 over Model 1.....	11.5	20.7	27.8	33.3	38.0	41.7
Sample size.....	2618	2346	2095	1855	1631	1427

Thus, higher Model 5 errors in Table 11 compared to the counterpart table in the NHC83 model, are entirely an artifact of the different CLIPER models between the two basins. When these differences are accounted for, the two models have similar performance characteristics although the errors from JTWC92 are slightly less than for NHC83.

7.3 PERFORMANCE ON OTHER THAN DEVELOPMENTAL DATA

Running a statistical model on an independent data set serves two purposes. Errors from the set are generally higher and are typically somewhat closer to what might be expected on purely operational data. Also, such a test is used to determine that the model is functioning as expected. Such a test is rather inappropriate for statistical-dynamical models where the use of perfect-prog methodology produces fictitiously low errors on either dependent or independent data. Also, the model was patterned after the NHC83 model which has been thoroughly tested on all types of data. Accordingly, a test of model performance on a classical "independent" data set was not conducted at this phase of model development.

Nevertheless, in that certain aspects of the model (for example, the use of Model 4 to estimate forecast positions) are only used under operational conditions, it was considered prudent to run the model under simulated operational conditions. Accordingly, a test was conducted whereby FNOC fields (in the Perfect-Prog mode) were supplied to the model. Also, initial and past storm positions were obtained from the best-track. The test indicated that the model was functioning as expected.

8. ACTIVATING JTWC92 IN AN OPERATIONAL MODE

8.1 REVIEW

The derivation and special features of the statistical-dynamical JTWC92 model have been described. The model was patterned after the National Hurricane Center NHC83 and NHC90 models. As has been shown, performance characteristics of JTWC92, based on developmental data, are quite similar to the NHC models. Although this suggests that performance in an operational mode should also mimic NHC83 performance, much depends on the characteristics of

the initial analysis and numerical model which supply deep-layer-mean geopotential heights, through the 72h projection, to the JTWC92 model.

8.2 A STATISTICAL PITFALL

Fig. 4 presented composite height fields for the North- and South-Zones. Here, it can be noted that the vortex is only weakly included in the analysis. Also, there is a slight bias (see Section 5.2.5) in positioning of the vortex. The retained predictors (see Figs. 11, 12 and 13) reduce the variance of tropical cyclone motion in that they sense the large scale environmental "steering" pattern and are located outside of the vortex circulation. As with any statistical model, it is assumed that the attributes of overall height pattern will remain the same when activating the model in an operational mode (Neumann et al., 1979). Violation of this assumption is a classical statistical pitfall.

Two recent innovations in numerical models might be problematical in regard to predictor location: bogussing and increased spectral model resolution. Bogussing refers to an enhancement and correct positioning of the tropical cyclone vortex while resolution refers to the scale of the analysis features which a numerical model can address.

Both of the above innovations may well increase the size of the vortex as well as stimulate the numerical model to retain and project the vortex downstream. In that one or more of the JTWC92 predictors might fall inside of the projected NOGAPS tropical cyclone circulation, misleadingly low heights could be indicated at one or more of the forecast intervals. This could seriously impair JTWC92's ability to sense the larger scale background steering patterns which it was designed to do. There would be a tendency for JTWC92 to rotate about the NOGAPS tropical cyclone center. This problem has been noted in the Atlantic basin when the NHC83/NHC90 models have been provided with output from higher resolution numerical models in which the initialization procedures have included bogussing of the vortex. It has also been noted in semi-operational testing of JTWC92 on NOGAPS 1990 archived fields.

In view of the above, every effort must be made to provide JTWC92 with analyses and prognoses fields having features similar to those depicted in Fig. 4. This might be accomplished by truncating higher resolution models at some lower wave number. However, tests on independent 1990 NOGAPS Deep-Layer-Mean fields show that extreme truncation is required to completely remove the tropical cyclone vortex. This has the undesirable side-effect of adjusting other analysis features, important to the JTWC92 model. Accordingly, some other method should be employed or developed to remove the tropical cyclone vortex without influencing the analysis outside of the storm domain.

8.3 COLD BIAS?

The analysis used in developing JTWC92 are considered to have zero bias, even though some bias may, indeed, be introduced by "first-guess" fields. Some numerical models introduce substantial bias which may be a function of pressure, projection and synoptic regime. This is typically a cold bias with geopotential heights being forecast too low. Saha and Alpert

(1988) discuss such a bias pattern with respect to the National Meteorological Center Medium Range Forecast (MRF) model. In the NHC83 model (Neumann, 1988b), it was necessary to correct for this systematic bias pattern in the MRF model. Provisions for bias correction have not been included in the JTWC92 model since NOGAPS biases are reasonably low (Hogan and Rosmond, 1991).

8.4 PROGRAM OPTIONS

Provision will be made in the computer coding of the JTWC92 model for selecting certain program options. One of these is the number of feedback iterations or iteration index (see Section 3.6) to be used. This value has been objectively set to three but might need to be adjusted after running the program in an operational mode for at least one typhoon season. Rationale prompting the initial index setting of three is discussed in Appendix B.

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APPENDIX A

(LIST OF ACRONYMS)

CLIPER.....CLImatology and PERsistence
CSUM.....Colorado State University Model
CPU.....Central Processing Unit
DLM.....Deep Layer Mean
FNOC.....Fleet Numerical Oceanography Center
HPAC.....Half Persistence And Climatology
JTCW.....Joint Typhoon Warning Center
NHC.....National Hurricane Center
NMC.....National Meteorological Center
NRL.....Navy Research Laboratory
NOARL.....Navy Oceanographic and Amospheric Research Laboratory
NOGAPS.....Navy Operational Global Analysis and Prediction System
PP.....Perfect-Prog
WESPAC.....WEStern PACific

APPENDIX B

Optimizing Number of Program Iterations

Proper setting of the number of program iterations (iteration index) is an important consideration in the JTWC92 model. Too few iterations will result in larger forecast error while too many iterations will consume excess computer time and may also result in larger forecast error. While an optimum setting depends on the given forecast situation, the setting to be used here will be optimized with respect to the dataset as a whole. The iteration concept was discussed in Section 3.6 where it was pointed out that setting the iteration index is a program option and that the recommended setting is 3. The justification for this recommendation is discussed in this addendum.

The necessity for setting the program iteration counter is only encountered when activating JTWC92 in an operational mode as opposed to the developmental or research mode of the program (see Section 3.6). Ideally, an extended record of 72h forecasts using operational input data and current NOGAPS prognoses would be used to determine the optimum setting of the index. However, such data are not available. Accordingly, the program was activated in the operational mode but using developmental, rather than operational data.

To determine the number of iterations associated with minimum forecast error, the program was activated on each appropriate forecast situation in the data set and a record was kept of the individual and collective forecast error. This process was repeated with the iteration index alternately set from 1 to 5.

In that the test consumed a very large amount of computer time, only those cases having a full verifiable 72h track were used. Another restriction was that the storm be of tropical storm or typhoon intensity throughout the 72h forecast period. For the latter reason, the sample sizes utilized in the test were somewhat less than those specified in Table 2b for the 72h projection.

The results of the test are shown in Table B1. For the short range projections, it can be noted that the forecast errors are less than those given in Tables 8 through 11. This is a consequence of a forecast error bias being introduced in the test by excluding forecasts not having a full 72h track. Forecast errors tend to be higher at the end of the forecast track where, for verification purposes, a full 72h projection is not available. The following conclusions can be drawn from the test:

- The iteration setting has minimum effect on the short-range forecasts and maximum effect on the long-range forecasts.
- The setting has greater effect on "North-zone" storms than it does on "South-zone" or on "Equatorial-zone" storms.
- The optimum number of iterations (minimum forecast error) is greater with increased projection.

- The decrease in forecast error with increasing number of iterations appears to be asymptotic.
- All factors considered (see below), the optimum number of iterations appears to be 3.

Discussion - From the table, minimum forecast error appears to be associated with a number of factors and is not possible to select a unique value which would be optimum in all situations. Another consideration is that the computer time needed to run the program increases with increased number of iterations. Although the number of iterations could be made a function of

Table B1. Determination of optimum number of program iterations. Shown are J1WC92 forecast errors (nmi) for specified zone(s) and for specified number of program iterations (I) with model being activated in an operational mode but with developmental data. Minimum error in each column for given zone is in boldface type. Sample includes only those cases where full 72h track was available (see text).

		12h	24h	36h	48h	60h	72h
NORTH-ZONE N = 428	I=1	34.0	74.0	121.0	174.0	246.0	327.0
	I=2	33.0	73.0	114.0	156.0	207.0	269.0
	I=3	33.0	72.0	113.0	153.0	198.0	253.0
	I=4	33.0	73.0	114.0	154.0	198.0	247.0
	I=5	33.0	73.0	114.0	154.0	198.0	249.0
SOUTH-ZONE N = 670	I=1	30.6	64.2	99.8	138.8	185.2	250.3
	I=2	30.6	63.3	97.3	131.9	171.4	223.0
	I=3	30.6	63.3	97.0	131.4	170.6	219.0
	I=4	30.6	63.3	97.1	131.7	170.9	217.7
	I=5	30.6	63.3	97.1	131.9	171.3	219.5
EQUATORIAL-ZONE N = 300	I=1	34.9	72.4	110.6	144.5	173.8	204.0
	I=2	34.9	72.4	110.2	142.2	170.6	200.2
	I=3	34.9	72.4	110.2	142.1	169.8	198.3
	I=4	34.9	72.4	110.2	142.2	169.8	198.3
	I=5	34.9	72.4	110.2	142.2	169.8	198.2
ALL ZONES COMBINED N = 1398	I=1	32.6	68.9	108.5	150.5	200.6	262.5
	I=2	32.3	68.2	105.1	141.3	181.7	231.4
	I=3	32.3	67.9	104.7	140.2	178.5	224.4
	I=4	32.3	68.2	105.0	140.6	178.6	222.0
	I=5	32.3	68.2	105.0	140.7	178.8	223.4

zone and projection, the increased program complexity and computer time would probably not justify this action. Accordingly, a value of three was selected as a satisfactory compromise.

Since the higher number of iterations is associated with the extended projections and on the more poleward storms, this suggests that the optimum number of iterations is dependent on the amount of recurvature. This further suggests a procedure whereby the number of iterations be made a function of the forecast situation. However, such a possible refinement is not included in this version of the model.

CHAPTER 3

A REVISED CLIMATOLOGY AND PERSISTENCE MODEL (WPCLPR) FOR THE
PREDICTION OF WESTERN NORTH PACIFIC TROPICAL CYCLONE MOTION,
by Charles J. Neumann

**A REVISED CLIMATOLOGY AND PERSISTENCE MODEL (WPCLPR) FOR
THE PREDICTION OF WESTERN NORTH PACIFIC TROPICAL CYCLONE MOTION**

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A REVISED CLIMATOLOGY AND PERSISTENCE MODEL (WPCLPR) FOR THE PREDICTION OF WESTERN NORTH PACIFIC TROPICAL CYCLONE MOTION

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ABSTRACT

The derivation and operational characteristics of a new statistical CLIPER-type model for the Western N. Pacific basin are described. Although the model is similar to an earlier model developed by Xu and Neumann (1985), it does not have the temporal and spatial restrictions associated with that earlier model.

The new model was specifically structured as part of a larger scale effort: the development of a statistical-dynamical model (JTCW92) for the Western N. Pacific basin. WPCLPR is needed as input to JTCW92.

Also included is the listing of the FORTRAN program which is needed to activate the model. Various constants needed by the program are included as BLOCK DATA subprograms.

1. INTRODUCTION

1.1 PURPOSE

This statistical model (WPCLPR) was structured as part of a larger effort: the development of a new statistical-dynamical model (JTCW92) for the Western N. Pacific (WESPAC) tropical cyclone basin. JTCW92 requires the output of a CLIPER (CLImatology and PERSistence)-type model as part of the prediction algorithm. Although WPCLPR is very similar to an earlier CLIPER-type model (Xu and Neumann, 1985) for WESPAC, two qualifications in that version of the model discouraged its use as part of the JTCW92 model: (1) the developmental data included only those storms initially located between latitudes 5N and 35N and longitudes west of 150E and (2) only those storms occurring between 15 May and 15 December. Since the intent was to allow activation of JTCW92 on all WESPAC tropical storms regardless of temporal or spatial considerations, removal of these restrictions from the model was needed. This was more profitably accomplished through a complete model revision rather than by redressing the old model. Structuring of the revised WPCLPR model is described herein.

1.2 BACKGROUND

Models based on climatology and/or persistence are widely used at the various Forecast Centers. Subsequent to the development of an Atlantic CLIPER model (Neumann, 1972), similar types of models were gradually developed

¹ This, and an associate document which describes the JTCW92 model (Neumann, 1992), was prepared under Contract Number N00014-90-C-6042.

for the other basins. Some of these include Neumann and Randrianarison (1976) for the SW Indian Ocean, Neumann and Leftwich (1977) for the Eastern North Pacific, Neumann and Mandal (1978) for the North Indian basin and Xu and Neumann (1985) for the Western N. Pacific.

Through the use of stepwise screening regression methodology, CLIPER-type models attempt to obtain an optimum blend of climatology and persistence for predictive purposes. In some areas where motion is rather steady (i.e., the Eastern North Pacific basin) or where environmental data is poor or lacking, it is difficult to improve over this type of forecast. However, in basins or portions of basins where tropical cyclone motion is erratic, forecast errors from such models can be substantial.

Since the ability to profitably use climatology and persistence varies considerably from basin to basin, CLIPER models are widely used as "benchmarks" from which to assess another model's ability to improve over climatology and persistence. Indeed, Pike and Neumann (1987) used the concept to compare "forecast difficulty" from one basin to another. They showed that, other factors being equal, forecast errors are likely to be higher over some basins than others.

CLIPER models are based on historical storm tracks. Input to such models are typically the datetime and a storm's initial position and positions at -12 and -24h; the latter being used to determine past motion of the storm. In some CLIPER models (i.e., the N. Atlantic basin), current and past motion is supplied by the forecaster rather than being computed from present and past positions. Additionally, some CLIPER models use maximum surface wind as a predictor although the incremental reduction of variance obtained from the latter is rather small although still significant in the statistical sense.

2. DEVELOPMENTAL DATA

2.1 BEST-TRACKS AND DATA EXCLUSIONS

A very large data set was available from which to develop the model. This consisted of the WESPAC best-tracks² (positions and maximum surface wind at 6-hourly intervals) over the 44-year period, 1945 through 1988 as obtained from the Joint Typhoon Warning Center in Guam. A few storms, initially located poleward from 50N were excluded as were storms initially located east of 180 degs longitude. As is typical with other CLIPER models, cases were also excluded if the storm, either at the initial or the final position, was below tropical storm intensity.

Since the prediction algorithm requires -12h and -24h storm positions, it was also necessary to exclude the early portions of some tracks. However, many of the latter were already excluded because of the ≥ 34 knot intensity requirement. A few early storms, lacking maximum wind information,

² The best-track is the accepted track of the storm after a complete post-analysis.

were also excluded. Finally, an independent data set, consisting of approximately one year of cases (455 cases at the 12h projection), was randomly selected and reserved for eventual independent testing of the model.

2.2 SAMPLE-SIZE

After the exclusions noted above, there remained a total of 18891, 16851, 14979, 13224, 11598, 10094 cases at 12 through 72h, respectively for development of the WPCLPR model. In that the above cases were taken at 6-hourly intervals, they are obviously not independent in the temporal sense and the actual degrees of freedom would be much less than the sample size (Neumann et al., 1977). Nevertheless, the very large data base assures that adequate degrees of freedom are available consistent with the rather large number of predictors used in the prediction algorithm.

3. MODEL DEVELOPMENT

3.1 PREDICTANDS

To be predicted using classical multivariate regression concepts are the orthogonal [meridional (P_m) and zonal (P_z)] storm displacements at 12h intervals, 12 through 72 hours. All distances (in nautical miles) were computed in the great circle sense using navigational programs developed by Taylor (1982). This is consistent with navigational methodology used throughout the JTWC91 algorithm.

3.2 THE 8 BASIC PREDICTORS

3.2.1 Definitions of Basic Predictors - Similar to those used in the earlier Xu and Neumann (1985) version of WPCLPR, eight basic predictors (P1 through P8) were defined:

- P1 Initial storm latitude;
- P2 Initial storm longitude;
- P3 Julian day number function;
- P4 Meridional displacement over past 12h (nmi);
- P5 Zonal displacement over past 12h (nmi);
- P6 Meridional displacement over past 24h (nmi);
- P7 Zonal displacement over past 24h (nmi);
- P8 Maximum wind (knots).

P4 through P7 are stated in different units (distance, rather than speed) than in Xu and Neumann (1985) in order to be consistent with the JTWC91 algorithm.

3.2.2 Day Number Function - Predictor P3 (Day number function) was also defined differently than in the Xu and Neumann study where the simple Julian Day Number (JDN) itself was used as the function. However, that model was valid only from May 15 (JDN 135) through December 15 (JDN 349). In that the current model includes all JDN's from 1 through 365, this results in a forecast track discontinuity when going from JDN 365 to JDN 1. This was considered to be an undesirable feature for forecasts on storms which occasionally occur over WESPAC in late December.

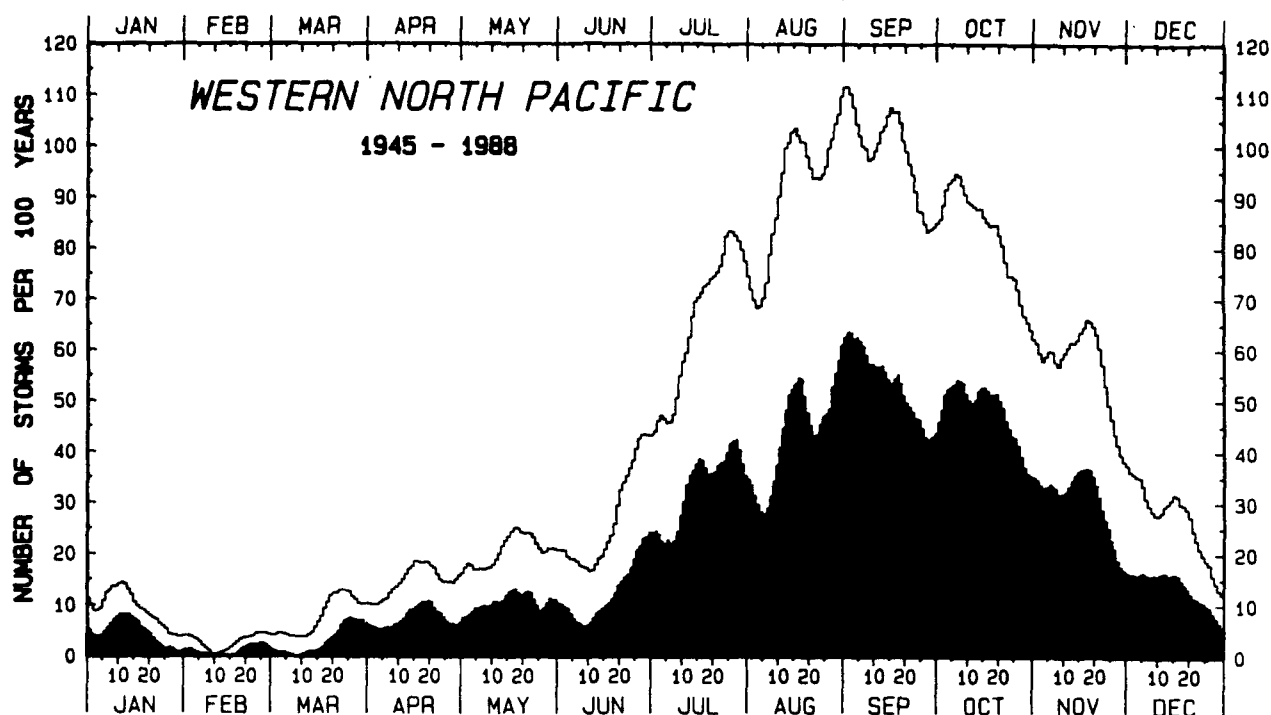


Fig. 1. Daily expectancy of tropical cyclones having at least tropical storm intensity (upper bound) and at least typhoon intensity (lower bound). Data have been smoothed over centered 9-day periods.

Two methods were used to avoid the problem. It can be noted in Fig. 1 that the minimum of annual storm activity for WESPAC is near Feb. 10 (JDN 41). Accordingly, 41 days were subtracted from all JDN's. There is only a small chance that a storm would straddle this period. Further tests with the developmental data indicated that the mathematical sine of the offset JDN provided for still greater variance reductions. Accordingly, a function was defined,

$$P3 = \text{SIN}[(\text{Day Number} - 41) * \pi / 364.75].$$

Minimum value (zero) occurs on Feb. 10 and maximum value (1.0) of the function occurs on August 12. A value of 0.5 occurs near April 12 and December 12.

3.2.3 Statistical Properties of Basic Predictors - Table 1 presents the means and standard deviations of the 2 predictands and the 8 basic predictors. The smaller sample sizes with increased forecast interval are associated with storms being dropped from the developmental data set for one of several reasons such as the storm dissipating or becoming extratropical. As noted in the Table, this leads to somewhat different data attributes for the different projections. For example, the average initial storm latitude (P1) of 20.4N at 12h and 17.7N at 72h reflects the fact that storms at low latitudes are more likely to endure through 72h than are storms at high latitudes.

3.2.4 Correlation Matrices - Linear correlation coefficients between 12h predictands and the 8 basic predictors as well as inter-correlations are presented in Table 2. Here, as would be expected, maximum correlation for a given component of motion is between future motion and past motion and these predictors or one of their higher order cross-product derivatives are always selected as the initial predictor. Hence, the importance of specifying a best-track scale of past storm positions when activating the program in an operational mode (see Section 6.1).

Table 1. Means and Standard Deviations (in parenthesis) of the 2 predictands and 8 basic predictors used in development of the Western North Pacific CLIPER model. Winds are in knots and displacements are in nautical miles. Mean zonal displacements (negative) are towards west. Mean meridional displacements (positive) are towards north.

	12 Hour	24 Hour	36 Hour	48 Hour	60 Hour	72 Hour
Pm Meridional Displacement	71.3 (73.1)	143.6 (137.9)	215.5 (197.1)	286.7 (250.2)	356.7 (299.0)	424.0 (343.5)
Pz Zonal Displacement.....	-30.1 (119.8)	-63.1 (226.3)	-98.4 (322.0)	-135.5 (407.4)	-172.7 (484.4)	-210.7 (553.8)
P1 Initial Latitude.....	20.4N(7.6)	19.8N(7.1)	19.3N(6.8)	18.7N(6.4)	18.2N(6.1)	17.7N(5.9)
P2 Initial Longitude.....	134.6E(14.2)	135.0E(13.6)	135.4E(13.2)	136.0E(12.8)	136.6E(12.5)	137.3E(12.3)
P3 Day Number Function....	0.839 (0.193)	0.840 (0.191)	0.840 (0.191)	0.839 (0.190)	0.839 (0.190)	0.838 (0.189)
P4 -12h Meridional Displacement.....	64.3 (64.5)	61.3 (60.5)	58.3 (56.7)	54.9 (52.9)	52.0 (50.0)	49.3 (48.2)
P5 -12h Zonal Displacement.....	-41.7 (109.4)	-48.7 (101.5)	-55.1 (94.1)	-60.7 (88.2)	-65.3 (83.5)	-69.6 (79.0)
P6 -24h Meridional Displacement.....	122.4 (116.4)	116.9 (109.5)	111.1 (102.7)	105.0 (96.3)	99.8 (91.8)	94.6 (88.1)
P7 -24h Zonal Displacement.....	-93.7 (204.8)	-106.6 (190.2)	-118.1 (177.2)	-128.2 (166.9)	-136.6 (158.2)	-143.8 (150.5)
P8 Maximum wind.....	73.5 (28.1)	75.7 (28.4)	77.1 (28.9)	77.9 (29.3)	78.4 (29.7)	78.4 (30.1)
N Sample size	18891	16851	14979	13224	11598	10094

*Note: This is approximately equivalent to June 6 and October 18.

Table 3 gives these same data for the 72h projection. Here, as would similarly be expected, most of correlations between predictands and predictors are considerably lower at 72h than they are at 12h.

In that Table 2 and 3 sample sizes are so large even after allowing for serial correlation, only those correlations near zero are not significant. For example, for 1000 cases, the critical 99% level of significance of the correlation coefficient is about 0.08.

Tables 2 and 3 are only valid for the selection of an initial predictor. Subsequent predictors are selected on the basis of partial correlation fields (Mills, 1955) given that the previous predictor(s) have already been selected.

3.3 HIGHER-ORDER PREDICTORS

The intent is to set up a statistical relationship between storm motion and the 8 basic predictors such that,

$$P_m = f_1(P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8) \text{ and} \quad (1)$$

$$P_z = f_2(P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8). \quad (2)$$

Functions f_1 and f_2 are typically taken as simple polynomials with the order of the polynomial being dependent on the complexity of the tracks and the sample size. The large data base and the parabolic nature of storm tracks over WESPAC led to the selection of a 3rd-order polynomial such as was used in Xu and Neumann (1985).

The number of terms (T) (including the intercept value) in a polynomial expansion of functions such as (1) and (2) is given by,

$$T = (m + n)! / (m!n!), \quad (3)$$

Table 2. Linear correlation coefficient matrix for WPCLPR 12h developmental data set. Sample size was 18,891 cases.

	PM	PZ	P1	P2	P3	P4	P5	P6	P7	P8
PM +12h Meridional Displacement....	1.000									
PZ +12h Zonal Displacement.....	.487	1.000								
P1 Initial Latitude.....	.452	.602	1.000							
P2 Initial Longitude.....	.178	.232	.219	1.000						
P3 Day Number Function.....	.121	.017	.459	-.060	1.000					
P4 -12h Meridional Displacement....	.805	.460	.507	.184	.112	1.000				
P5 -12h Zonal Displacement.....	.418	.908	.599	.281	.037	.419	1.000			
P6 -24h Meridional Displacement....	.750	.477	.544	.197	.110	.953	.429	1.000		
P7 -24h Zonal Displacement.....	.383	.872	.604	.305	.052	.394	.979	.409	1.000	
P8 Maximum wind.....	.046	-.110	-.046	-.021	-.002	.033	-.142	.028	-.156	1.000

Notes: (1) PM and PZ are predictands; P1 through P8 are primary predictors.

(2) East longitudes were defined as positive.

(3) Day number function defined as $\text{SIN}[(\text{Day Number} - 41) * \pi/364.75]$ (see text).

Table 3. Linear correlation coefficient matrix for WPCLPR 72h developmental data set. Sample size was 10,094 cases.

	PM	PZ	P1	P2	P3	P4	P5	P6	P7	P8
PM +72h Meridional Displacement....	1.000									
PZ +72h Zonal Displacement.....	.591	1.000								
P1 Initial Latitude.....	.261	.531	1.000							
P2 Initial Longitude.....	.055	-.094	.011	1.000						
P3 Day Number Function.....	.124	.078	.545	-.076	1.000					
P4 -12h Meridional Displacement....	.507	.398	.275	.065	.075	1.000				
P5 -12h Zonal Displacement.....	.225	.615	.470	.050	.153	.189	1.000			
P6 -24h Meridional Displacement....	.463	.397	.306	.068	.077	.936	.181	1.000		
P7 -24h Zonal Displacement.....	.200	.568	.468	.080	.164	.173	.972	.168	1.000	
P8 Maximum Wind.....	.189	.090	.133	-.044	.004	.137	-.067	.134	-.080	1.000

Notes: (1) PM and PZ are predictands; P1 through P8 are primary predictors.

(2) East longitudes were defined as positive.

(3) Day number function defined as $\text{SIN}[(\text{Day Number} - 41) * \pi/364.75]$ (see text).

where m is the number of basic predictors and n is the order of the polynomial. From (3), it follows that a 3rd order-polynomial having eight basic predictors will contain 165 terms (164 predictors and 1 intercept value). In practice, these additional predictors can be generated by considering all possible 3rd-order products and cross-products of the 8 basic predictors.

3.4 PREDICTOR SELECTION

3.4.1 Selection Procedure - Not all of the potential 164 predictors are used in the model. Classically, predictors are systematically selected until the incremental reduction of variance drops to some preset value, typically taken as 1/2%. The problem with this approach is that some predictors that may be working in combination are overlooked in the screening methodology used here which looks at only one predictor at a time.

Another problem in predictor selection is that prediction equations from one time period to another are structured independently and there is no

guarantee that the same set of predictors will be chosen for each time period. This gives rise to the generation of non-realistic "meandering" tracks which are not realistic in the best-track sense and impart a certain degree of user skepticism to the forecast.

The above potential problems led to the following procedure in predictor selection:

- (1) Run the screening program for meridional motion and select the same number (N) predictors with N being determined by experimentation (see Step 5).
- (2) For all projections, 12 through 72h, note predictors used at least once and rerun screening program for each projection, forcing in those predictors and excluding all other predictors.
- (3) Follow steps (1) and (2) for zonal component of motion.
- (4) Compute net forecast error from independent data set (see Table 7) with given N.
- (5) Repeat steps (1) through (4) with different value of N.

In Xu and Neumann (1985), the optimum value of N was determined to be 20 and, as a starting point, N was initially assigned this value. Next, steps (1) through (4) were repeated with values of N equal to 10, 25, 30, 35, 40 and 164. Minimum forecast error on the developmental data set was obtained with an N of 30. Accordingly that value was used in the revised model rather than the 20 as in Xu and Neumann (1985). This resulted in 90 common predictors [step (2)] for meridional motion and 95 common predictors for zonal motion. Thus, the general form of the prediction equations are,

$$D_m = A_0 + \sum_{i=1}^{i=90} (A_i P_i) \quad \text{and} \quad D_z = B_0 + \sum_{i=1}^{i=95} (B_i P_i), \quad (4)$$

where, for a given projection 12 through 72h, D_m is forecast displacement distance in the meridional direction, D_z is forecast displacement in the zonal direction, arrays A and B are constants and P is the predictor number of the 164 possible predictors generated by the cubic polynomial expansion of (1) and (2).

Although this is a large number of retained predictors, the developmental data set is large enough to assure that poor predictors are assigned low partial correlation coefficients and resultant low regression coefficients.

3.4.2 Principal Predictors - The first four predictors selected in the screening process are specified in Table 4. The complete listing of selected predictors is given in the WPCLPR FORTRAN code in the block data subprogram BLKDT1 (Appendix A).

Table 4. Principal predictors. Specified are first 4 of 90 meridional and 95 zonal predictors numbers (Pnnn). Basic Predictors P1 through P8 are identified in Table 2. List of all possible predictors is contained in SUBROUTINE PSETUP of FORTRAN program (see Appendix A).

	12 Hour	24 Hour	36 Hour	48 Hour	60 Hour	72 Hour
MERIDIONAL	037,022,021,053	037,022,021,053	037,022,021,128	037,138,021,048	138,037,021,022	138,037,022,161
ZONAL	022,012,006,036	022,013,006,122	022,129,006,139	022,129,125,080	022,129,125,080	096,129,125,080
WHERE:						
P(006)=P7	P(012)=P6	P(013)=P6*P8	P(021)=P6*P6*P6	P(022)=P5	P(036)=P5*P5*P5	P(037)=P4
P(048)=P4*P5*P8	P(053)=P4*P4*P8	P(080)=P3*P3*P8	P(096)=P2*P5	P(122)=P1	P(125)=P1*P7	P(128)=P1*P6
P(129)=P1*P6*P8	P(138)=P1*P4*P8	P(139)=P1*P4*P7	P(161)=P1*P1*P6			

3.4.3 Multiple Correlation Coefficients and Standard Error - Multiple correlations associated with the developmental data after the retention of the 90 meridional and the 95 zonal predictors are given in Table 5. These correlations are slightly higher than those given by Xu and Neumann (1985)³ in their Table 1. Differences are apparently due to the higher standard deviations of tropical cyclone motion in the revised model associated with the addition of storms poleward of 35N.

Also given in Table 5 are the Standard Errors of Estimate for each of the two components of motion. Here it can be noted that higher standard errors for zonal motion are associated with higher correlation coefficients. The explanation here is that the standard deviations for zonal motion (specified in Table 1) are also higher and the three quantities, standard error (S_e), standard deviation (S_d) and the correlation coefficient (R_m) are related according to,

$$R_m = (1 - S_e^2/S_d^2)^{1/2}. \quad (5)$$

For example, for 12h zonal motion, the Standard error (from Table 5) and the Standard deviation (from Table 1) are 40.1 and 73.1 nautical miles, respectively. Thus, according to (5) the multiple correlation coefficient is 0.836 as is specified in Table 5 for that component of motion.

Table 5. Multiple correlation coefficients (R_m) and Standard Error of Estimate (S_e) based on developmental data set.

	12 Hour	24 Hour	36 Hour	48 Hour	60 Hour	72 Hour
MERIDIONAL MOTION						
Correlation	0.836	0.806	0.756	0.710	0.673	0.644
Standard Error (nmi)	40.1	81.9	129.3	148.7	221.9	263.8
ZONAL MOTION						
Correlation	0.932	0.916	0.895	0.871	0.845	0.817
Standard Error (nmi)	43.5	90.9	143.9	201.2	259.8	320.6

³ In Xu and Neumann (1985), the entries for meridional and zonal motion appear to have been inadvertently reversed, (i.e, the higher values of multiple correlation coefficient and standard error should be for zonal motion rather than for meridional motion as shown in their Table 1).

4. MODEL PERFORMANCE

4.1 PERFORMANCE ON DEPENDENT DATA

Table 6 gives some indication of performance of WPCLPR on the developmental data set. With the addition of storms poleward of 35N, the errors are slightly higher than those given by Xu and Neumann's (1985) Table 1 which excluded the more northerly as well as off-season storms.

Table 6 also contains an error stratification based on the initial intensity of the storm. Here, it can be noted that the more intense storms are associated with substantially less error. Apparently, such storms are confined more to the spatial centroid of the data set where forecast errors tend to be lower (Jarrell et al., 1978). Also, statistical models, in general, tend to have lower residual errors in such areas. Perhaps, other factors might also be responsible.

4.2 PERFORMANCE ON INDEPENDENT DATA

Approximately 1-year of randomly selected data had been withheld from the developmental data set (see Section 2.2). Model performance on this independent data set are given in Table 7. Only a slight increase in error is noted here which is typical for this type of comparison. The same error dis-

Table 6. Average forecast errors (nmi) on entire and specified subsets of developmental data set.

	12 hour	24 hour	36 hour	48 hour	60 hour	72 hour
All storms	45.2	97.6	157.0	219.1	280.3	340.8
Sample size	18891	16851	14979	13224	11598	10094
Tropical storms	49.8	107.7	173.9	246.0	305.3	366.9
Sample size	2441	1845	1377	1016	728	527
Typhoons	44.7	97.0	156.7	219.2	281.5	341.9
Sample size	11825	10686	9582	8504	7484	6497
Super Typhoons	43.8	94.7	151.9	211.4	272.2	333.9
Sample Size	4625	4320	4020	3704	3386	3070

parity noted in Table 6 (lower errors on more intense storms) can be noted in Table 7. Indeed, the differences in error at 72h, depending on intensity, are quite distinct although the sample size becomes rather small at this time frame.

5. SOME PERFORMANCE CHARACTERISTICS

In this section, we will consider some of the characteristics of the WPCLPR model. For this purpose, a series of illustrations (Figs. 2 through 8) show some typical forecast storm tracks under various initial conditions. In general, the response of the model is in accordance with climatological expectations as given by Miller et al., 1988 or by Xue and Neumann, 1984.

Table 7. Average forecast errors (nmi) on entire and specified subsets of an independent data set.

	12 hour	24 hour	36 hour	48 hour	60 hour	72 hour
All storms	45.7	104.4	171.3	232.8	291.3	349.8
Sample size	455	416	370	323	275	231
Tropical storms	46.8	112.5	213.3	272.1	376.3	528.9
Sample size	60	48	42	29	20	10
Typhoons	45.6	104.0	173.0	242.9	300.3	369.2
Sample size	276	256	230	203	170	144
Super Typhoons	45.8	102.0	149.2	197.5	253.4	290.2
Sample Size	119	112	98	91	85	77

5.1 SENSITIVITY TO TIME OF YEAR

In the climatological sense, the expected motion of a storm at a given position, a given intensity and having a given initial motion would be a function of the time of year; this being a reflection of the general environmental steering forces to be expected in that area. The model's ability to sense these average forces is shown in Fig. 2. Here, all input data were held constant except for the Julian day number. The resultant shift in track is clearly noted. In accordance with climatological expectations, recurvature into the westerlies within 72h can be expected early and late in the season but not during mid-season. Maximum westerly component occurs near mid-August.

Earlier (see Section 3.2.2), it was pointed out that the Julian day number is shifted by 41 days and converted into a sine function; the latter having identical values twice during the year. Thus, with other conditions being equal, the forecast track would be identical near, for example, mid-April and mid-December.

Fig. 2 does not include tracks for the months January, February and March. Although the model would certainly produce a forecast track for those dates, storms having the indicated motion do not typically occur at the given initial location during those months.

5.2 SENSITIVITY TO MAXIMUM WIND

It can be shown that tropical cyclones with higher wind speeds beyond some critical radii tend to move farther northwestward than otherwise (Elsberry et al, 1987, Section 4.3). Although WPCLPR does not directly address wind profiles, it does address storm intensity and there is a weak positive statistical relationship between storm size (as measured by the outer closed surface isobar) and storm intensity (Merrill, 1982). Also, weak storms tend to be steered more by the lower troposphere and intense storms more by a deep layer throughout the troposphere (Simpson, 1971). The net result of these factors, and probably others, is that the more intense storms tend to have a larger

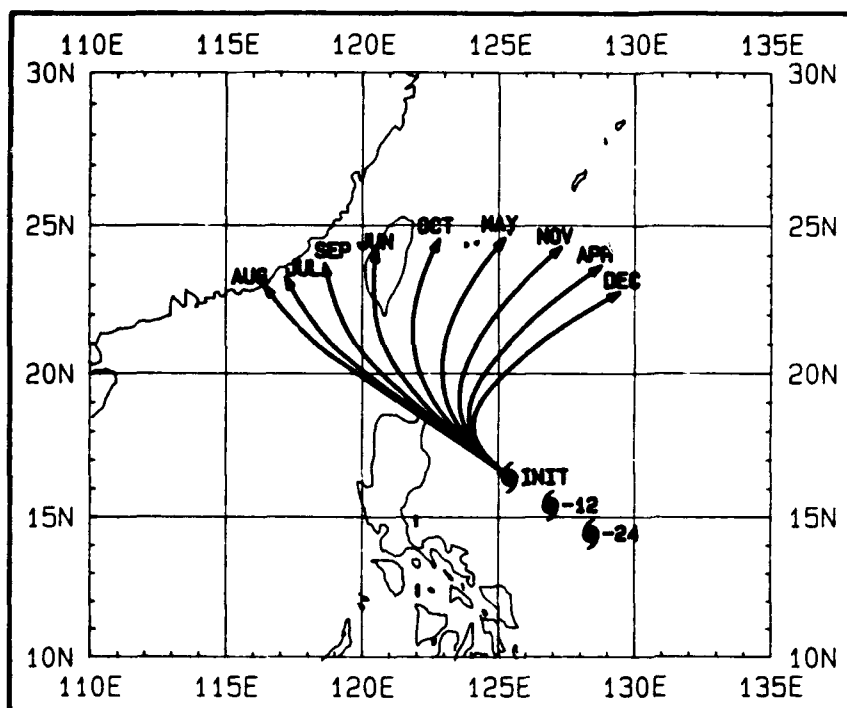


Fig.2. Sensitivity of WPCLPR to time of year. Shown are 72h forecast tracks on the 20th day of each month, April through December, with initial and past positions held constant as depicted by tropical cyclone symbols.

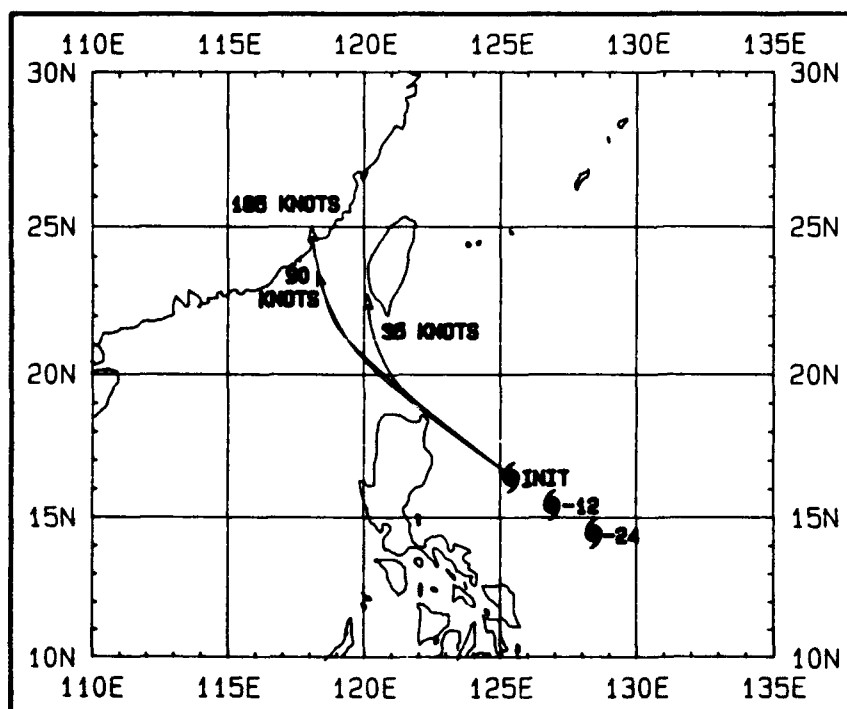


Fig. 3. Sensitivity of WPCLPR to maximum wind. Shown are 72h forecast tracks with three different initial storm intensities, 35, 90 and 185 knots. Initial, -12h and -24h positions have been held constant, as shown. Date is 15 September.

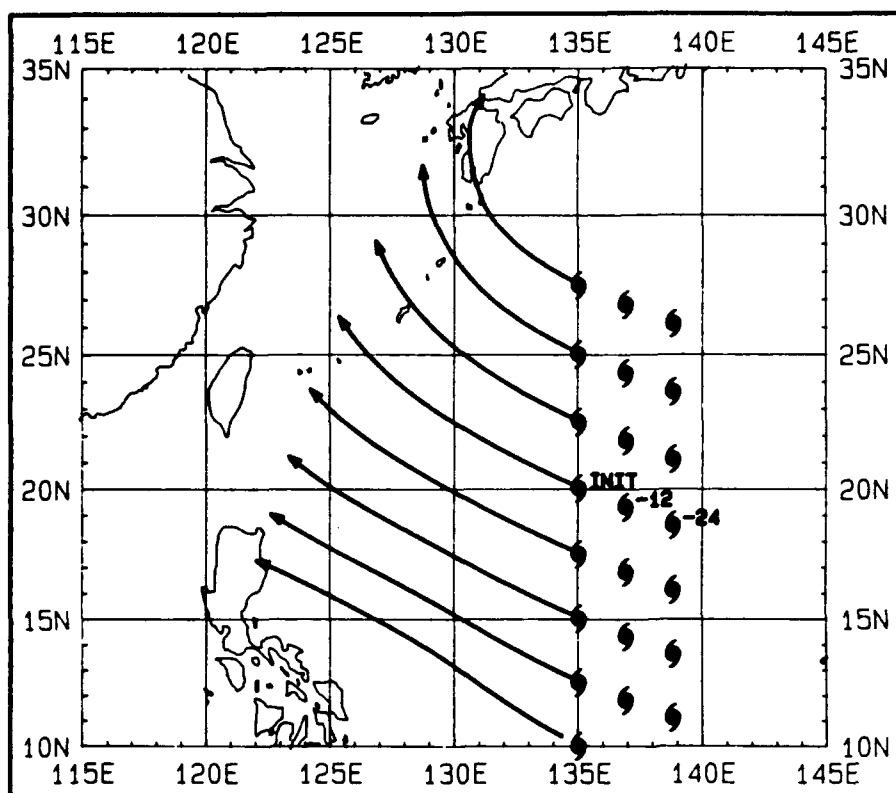


Fig. 4. Sensitivity of WPCLPR to initial latitude. Shown are 72h forecast tracks with specified initial, -12h and -24h storm positions. Date and storm intensity are 15 August and 100 knots, respectively.

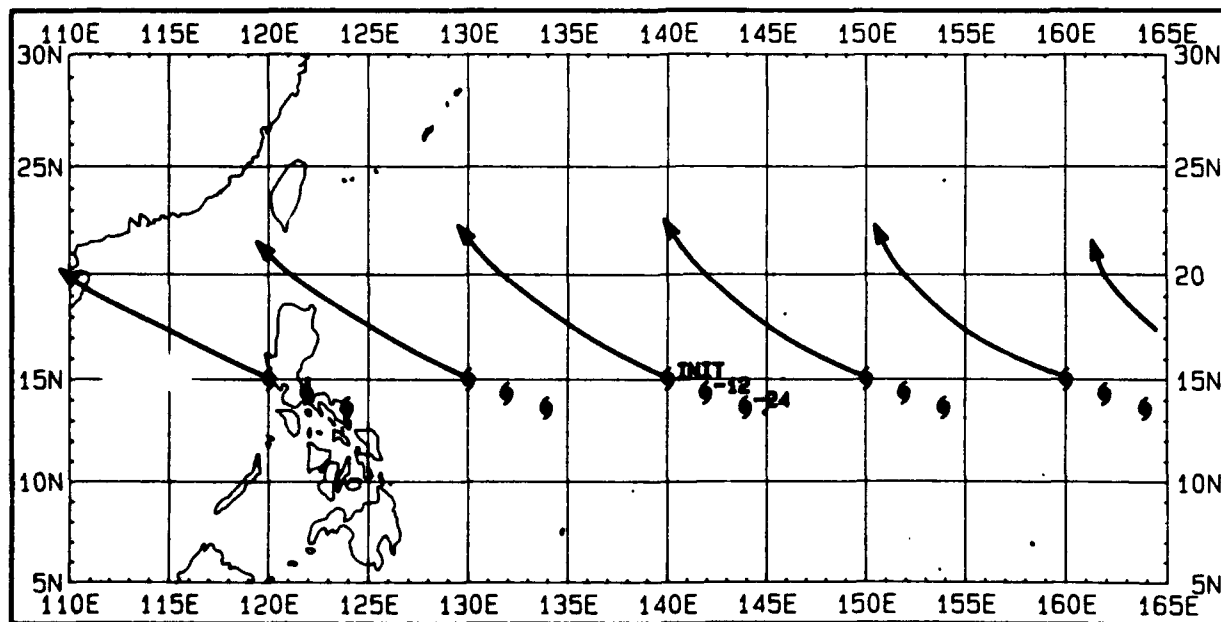


Fig. 5. Sensitivity of WPCLPR to initial longitude. Shown are 72h forecast tracks with specified -12h and -24h storm positions. Date and storm intensity are 15 September and 100 knots, respectively.

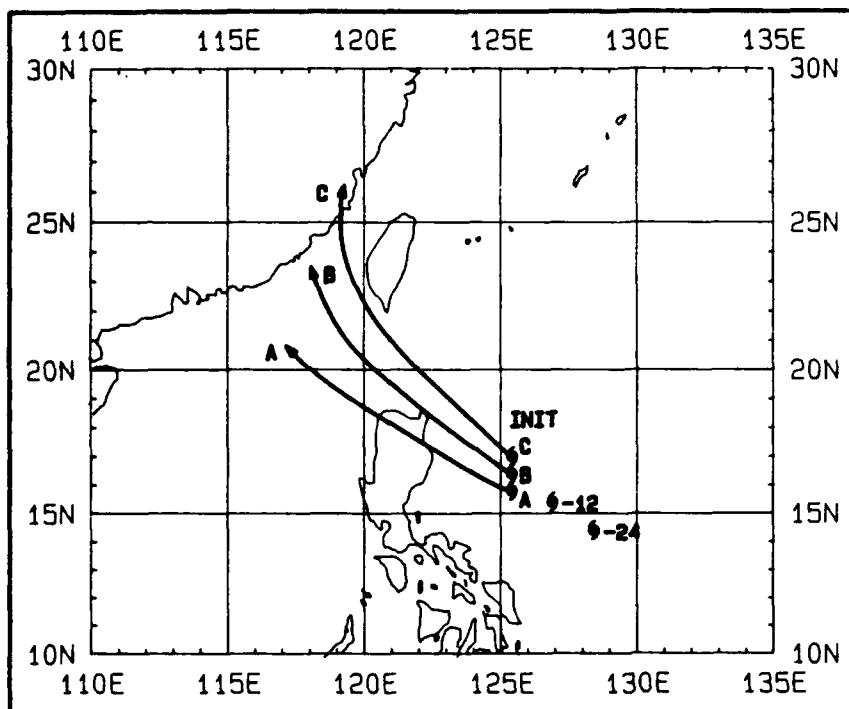


Fig. 6. Sensitivity of WPCLPR to initial position. Shown are 72h forecast tracks with specified initial, -12h and -24h positions. Date and storm intensity are 15 September and 100 knots, respectively.

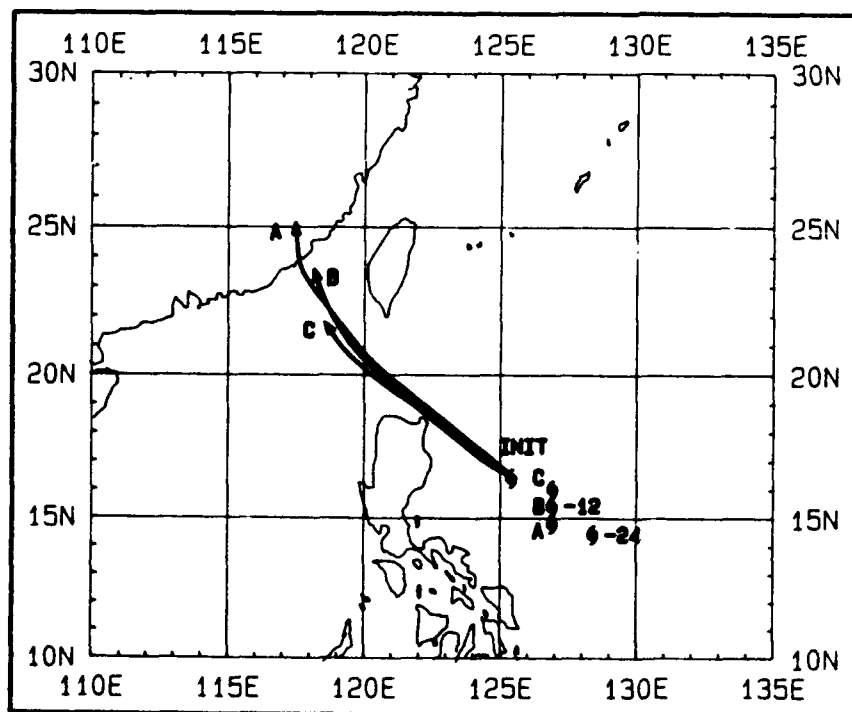


Fig. 7. Sensitivity of WPCLPR to 12h-old position. Shown are 72h forecast tracks with specified initial, -12h and -24h positions. Date and storm intensity are 15 September and 100 knots, respectively.

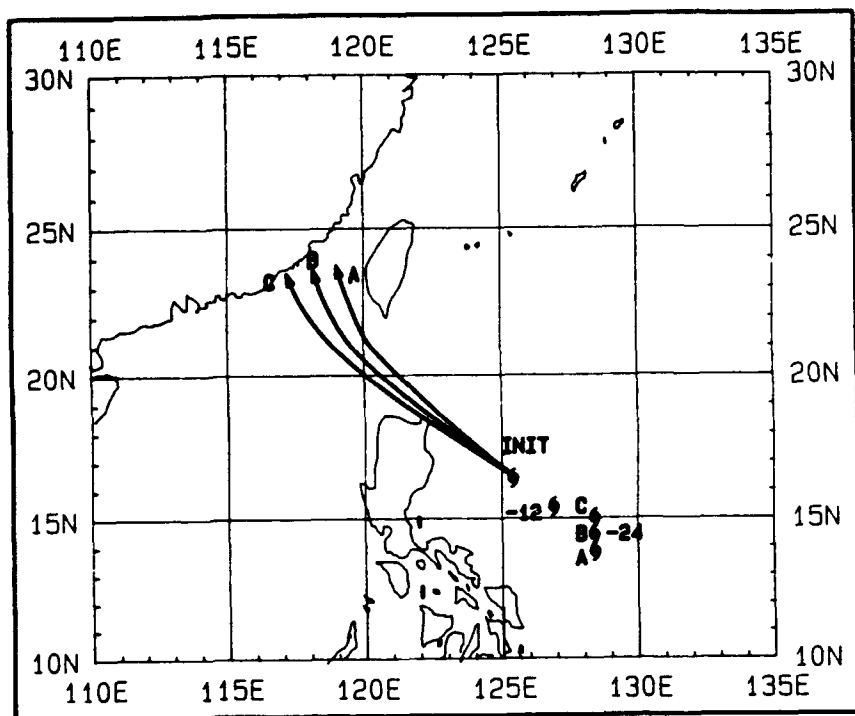


Fig. 8. Sensitivity of WPCLPR to 24h-old position. Shown are 72h forecast tracks with specified initial, -12h and -24h positions. Date and storm intensity are 15 September and 100 knots, respectively.

northwestward component than do the weaker storms. Fig. 3 demonstrates this effect in the WPCLPR model.

5.3 SENSITIVITY TO INITIAL POSITION

In the climatological sense, storms initially in the deep tropics are more likely to remain embedded in the easterlies (move with a continued westward component through 72h) than are storms initially at a more poleward latitude. Controlled WPCLPR forecasts, as illustrated in Fig. 4, agree with this expectation.

Additionally, there is a dependence on initial longitude although the effect is not as well defined as with initial latitude. This is depicted in Fig. 5 where storms initially located near the center of the basin are seen to move farther poleward through 72h than those at the extreme eastern end or the extreme western end of the basin.

5.4 SENSITIVITY TO INITIAL AND PAST MOTION

In addition to its use as a climatological predictor (predictors P1 and P2), the initial position of the tropical cyclone is used, together with the 12h old position, to determine the motion over the past 12 hours (predictors P4 and P5). As depicted in Fig. 6, the model is very sensitive to these latter two predictors. Here the initial motion was changed by keeping the past position constant but varying the initial position 0.6 degrees of latitude north (position C) and 0.6 degrees of latitude south (position A) from a presumed correct position B. The rather dramatic effect on the track is as shown.

The above experiment was also repeated by keeping initial and 24h old position constant and varying the 12h old position 0.6 degrees of latitude north and south of a presumed correct position. This is depicted in Fig. 7 Here, predictors P4, P5 P6 and P7 would all be affected. However, the effect of the shift is not as dramatic as occurs by only shifting the initial position.

Finally, Fig. 8 shows the effect on the 72h track forecast if only the 24h old position is varied as shown. Here, all predictors except P6 and P7 are held constant. It can be noted that the effect on the 72h track is relatively small compared to shifting the other positions as was shown in Figs. 6 and 7.

6. OPTIMIZING MODEL PERFORMANCE

6.1 INITIAL MOTION

The model was developed from best-track data. In the preceding section, it was noted that WPCLPR is very sensitive to the average motion vector over the past 12h as defined by the current and the 12h old positions. The forecaster must make every effort to assure that these positions reflect a best-track scale of motion. The methodology to accomplish this varies from one forecast center to another. To be avoided is the unqualified use of storm positions which reflect small-scale oscillations of the storm center which are not representative of the more conservative, larger scale motion of the entire storm envelop.

In this connection, the current estimate of the storm position need not automatically be the 12h-old position of a storm 12 hours later. The three sets of positions (current, 12h-old and 24-old) will require continuous adjustment so as to convey current motion trends to the model.

6.2 MODEL LIMITATIONS

Other than the requirement that the storm be initially located within the Western Pacific basin (west of 180 degrees longitude), there are no restrictions in activating the model. However, certain qualifications in interpreting the output should be noted.

In Table 1, it was shown that the sample size used in development of the model dropped from near 19,000 for the 12h forecast to near 10,000 for the 72h forecast. Many of the lost cases were on storms dropped from the data set as they moved poleward. Typically, these are fast moving storms. Thus, there is a bias towards the slower moving storms which remain in the data set. This bias shows up on storms which approach the poleward edge of the data set.

Consider, for example, Fig. 9, which shows the 72h forecast track on a northeastward moving storm initially located 27.5N, 137.5 on October 15. The forecast is quite consistent through the 48h projection but begins to deteriorate thereafter and is obviously severely biased at 72h. This reflects the loss of the faster moving storms cited in the preceding paragraph.

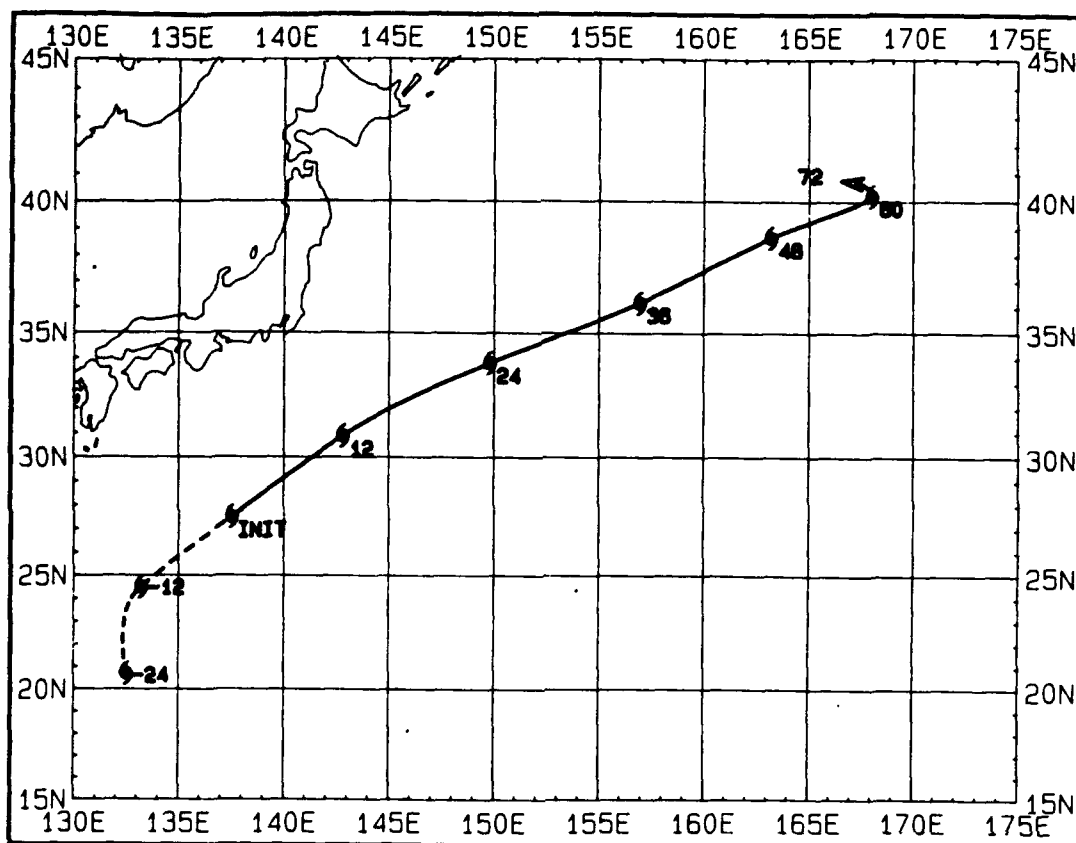


Fig. 9. Example of a biased WPCLPR track forecast on storm approaching northern geographical bounds of developmental data set. Date is 15 October and maximum wind is 90 knots.

7. TEST RUN OF PROGRAM

Appendix A contains a complete FORTRAN 77 listing of the programming code for the WPCLPR model. As a test, the program can be activated on the following input data from which track B of Fig. 8 was obtained.

```

IDATIM = 91091500
ALAT00 = 16.4
ALON00 = 125.4
ALAT12 = 15.4
ALON12 = 126.9
ALAT24 = 14.4
ALON24 = 128.4
WIND = 100.

```

Output from array (CNMIS(K),K=1,12) should be: 62.1,-87.0,127.5,
-173.0, 197.0, -254.4, 270.5, -326.8, 346.3,-372.7,423.0,-400.3

Output from array (CLALO(K),K=1,12) should be: 17.4, 123.9, 18.5,
122.4, 19.6, 120.9, 20.8, 119.6, 22.0, 118.7, 23.3, 118.1

Output from array (P1TOP8(K),K=1,8) should be: 16.4, 125.4, 0.958, 59.7, -86.8, 118.9, -174.4, 100.0

8. FINAL COMMENTS

8.1 OPERATIONAL USE OF MODEL

Although this revised version of WPCLPR was structured for use as input to another, higher-echelon, model, it could be used in the "stand-alone" sense. In that case, users will need to set up a MAIN calling program, perhaps in the interactive mode, for running of the model. Output, using the same example as in the previous Section, could be arranged as follows:

```
*****
INPUT: STORMNAME  89091500  16.4 125.4  15.4 126.9  14.4 128.4

      DISPLACEMENT (NMI)      POSITION      MOTION (DIR/SPD)
TIME  YRMODAHR      N+/S-  E+/W-  LATD  LONG  OVER LAST 12h

-24   89091400      118.9 -174.5  14.4N 128.4E  -----/-----
-12   89091412       59.7 -86.8  15.4N 126.9E  304.8/ 8.8 KTS
  00   89091500       0.0   0.0  16.4N 125.4E  304.9/ 8.8 KTS
+12   89091512       62.1 -87.0  17.4N 123.9E  305.5/ 8.9 KTS
+24   89091600      127.5 -173.0  18.5N 122.4E  306.7/ 9.0 KTS
+36   89091612      197.0 -254.4  19.6N 120.9E  309.5/ 8.9 KTS
+48   89091700      270.5 -326.8  20.8N 119.6E  313.7/ 8.6 KTS
+60   89091712      346.3 -372.7  22.0N 118.7E  326.6/ 7.4 KTS
+72   89091800      423.0 -400.3  23.3N 118.1E  337.5/ 6.8 KTS
*****
```

Here, users will need to supply additional subroutines for computing datetimes and storm motion.

8.2 COMPARISON WITH EARLIER VERSION OF WPCLPR

Although exhaustive testing has not been accomplished, indications are that this revised version of WPCLPR will perform similarly to the earlier version by Xu and Neumann (1985). This is evidenced by Figs. 2 through 9 where forecast motion is quite similar to that depicted in comparable graphics contained in the earlier study.

The main advantage of the newer version is that there are no restrictions in activating the model. Even though the few storms initially located north of 50N were excluded from the data set (see Section 2.1), tests indicate no particular problem in running the model at those latitudes other than the bias problem discussed in connection with Fig. 9.

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APPENDIX A

FORTRAN code for WPCLPR model

Contained in this section is a PC version of the FORTRAN computer code for the WPCLPR model. For mainframe usage, some minor modification may be required to the code. Activating the program is accomplished by a call to SUBROUTINE WPCLPR as follows:

```
CALL WPCLPR(IDATIM,ALAT00,ALON00,ALAT12,ALON12,ALAT24,  
$ALON24,WIND,CNMIS,CLALO,P1TOP8)
```

There are 11 arguments. First 8 are not dimensioned and must be supplied to program. Last three arguments are returned:

IDATIM (INTEGER*4) is in form YY/MO/DA/HR as 89052306,
ALAT00 and ALON00 are initial storm positions as 16.2, 135.4 (REAL*4),
ALAT12 and ALON12 are position 12h earlier (REAL*4),
ALAT24 AND ALON24 are position 24h earlier (REAL*4),
WIND is maximum wind near storm center in knots (REAL*4) as 95.

NOTES: It is assumed that latitudes are North and that longitudes are east. Initial longitude of 160W must be entered as 200.0. However, program has not been designed for initial positions in western hemisphere. All positions should reflect a best-track scale of motion.

Returned argument (CNMIS(K),K=1,12) gives the forecast storm displacements (negative towards west or south) in nautical miles where:

CNMIS(01) is 12h meridional and CNMIS(02) is 12h zonal displacement,
CNMIS(03) is 24h meridional and CNMIS(04) is 24h zonal displacement,
CNMIS(05) is 36h meridional and CNMIS(06) is 36h zonal displacement,
CNMIS(07) is 48h meridional and CNMIS(08) is 48h zonal displacement,
CNMIS(09) is 60h meridional and CNMIS(10) is 60h zonal displacement,
CNMIS(11) is 72h meridional and CNMIS(12) is 72h zonal displacement.

Returned argument (CLALO(K),K=1,12) are the above displacements converted to latitude and longitude starting from the initial position. All Longitudes are returned as positive east.

Returned argument (P1TOP8(K),K=1,8) gives values of the 8 basic predictors which can be utilized at user's discretion.

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FUNCTION F1.....	Page	A5
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BLOCK DATA BLKDT2.....	Pages	A6 - A7
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SUBROUTINE XY2LLH.....	Page	A23

SUBROUTINE WPCLPR(IDATIM,ALAT00,ALON00,ALAT12,ALON12,ALAT24,
\$ALON24,WIND,CNMIS,CLALO,P1TOP8)

C
C THIS IS CLIPER PROGRAM FOR WESTERN PACIFIC BASIN. THE FOLLOWING SHOULD
C BE NOTED:
C (1) PROGRAM WAS DEVELOPED USING STORM TRACKS OVER YEARS 1945-1988.
C (2) ALL MONTHS WERE INCLUDED IN DEVELOPMENTAL DATA SET.
C (3) STORMS INITIALLY LOCATED EAST OF 180 DEGS WERE EXCLUDED.
C (4) STORMS INITIALLY LOCATED NORTH OF 50N WERE EXCLUDED.
C (4) STORMS WHICH INITIALLY CLASSIFIED AS DEPRESSIONS OR CLASSIFIED AS
C DEPRESSIONS AT VERIFICATION TIME WERE EXCLUDED.
C (5) RESULTANT SAMPLE SIZE FROM ABOVE CRITERIA.....
C 18891 AT 12H, 16851 AT 24H, 14979 AT 36H,
C 13224 AT 48H, 11598 AT 60H, 10094 AT 72H.
C (6) INDIVIDUAL CASES IN DEVELOPMENTAL DATA SET WERE AT 6 HRLY INTERVALS
C (7) PROGRAM PREPARED BY CHARLES J. NEUMANN, SAIC, OCT NOV DEC, 1989.
C (8) THIS VERSION OF WPCLPR REPLACES EARLIER VERSION REPORTED ON BY
C XU AND NEUMANN (1985) IN NOAA TECHNICAL MEMORANDUM NWS NHC 28.
C EARLIER XU & NEUMANN VERSION HAD CERTAIN SEASONAL AND GEOGRAPHICAL
C RESTRICTIONS. CURRENT VERSION HAS NO RESTRICTIONS OTHER THAN AS
C NOTED ABOVE.
C
C INCOMING ARGUMENTS ARE AS FOLLOWS:
C IDATIM (INTEGER*4) IS IN FORM YY/MO/DA/HR AS 89052306
C ALAT00 AND ALON00 ARE INITIAL STORM POSITION (REAL*4)
C ALAT12 AND ALON12 ARE POSITION 12H EARLIER (REAL*4)
C ALAT24 AND ALON24 ARE POSITION 24H EARLIER (REAL*4)
C NOTE: IT IS ASSUMED THAT LATITUDES ARE NORTH AND THAT LONGITUDES
C ARE EAST. INITIAL LONGITUDE OF 160W MUST BE ENTERED AS
C 200 DEGREES. HOWEVER, PROGRAM HAS NOT BEEN
C DESIGNED FOR INITIAL POSITIONS IN WESTERN HEMISPHERE.
C WIND IS MAXIMUM WIND NEAR STORM CENTER IN KNOTS (REAL*4)
C
C RETURN ARGUMENT IS STORM DISPLACEMENTS IN NAUTICAL MILES AS GIVEN BY
C (CNMIS(J),J=1,12), LAT/LON POSITIONS AS GIVEN BY (CLALO(J),J=1,12)
C AND VALUES OF 8 BASIC PREDICTORS AS GIVEN BY (P1TOP8(K),K=1,8)
C
C ARRANGEMENT OF CNMIS AND CLALO ARRAY IS AS FOLLOWS:
C CNMIS(01) IS MERIDIONAL 12H DISPLACEMENT (NMI)
C CNMIS(02) IS ZONAL 12H DISPLACEMENT (NMI)
C CNMIS(03) IS MERIDIONAL 24H DISPLACEMENT (NMI)
C CNMIS(04) IS ZONAL 24H DISPLACEMENT (NMI)
C CNMIS(05) IS MERIDIONAL 36H DISPLACEMENT (NMI)
C CNMIS(06) IS ZONAL 36H DISPLACEMENT (NMI)
C CNMIS(07) IS MERIDIONAL 48H DISPLACEMENT (NMI)
C CNMIS(08) IS ZONAL 48H DISPLACEMENT (NMI)
C CNMIS(09) IS MERIDIONAL 60H DISPLACEMENT (NMI)
C CNMIS(10) IS ZONAL 60H DISPLACEMENT (NMI)
C CNMIS(11) IS MERIDIONAL 72H DISPLACEMENT (NMI)
C CNMIS(12) IS ZONAL 72H DISPLACEMENT (NMI)
C NOTE: NEGATIVE DISPLACEMENTS ARE TOWARDS WEST OR SOUTH.
C CLALO ARRAY CORRESPONDS TO CNMIS ARRAY EXCEPT THAT DISPLACEMENTS


```

C      HAVE BEEN CONVERTED TO LATITUDES NORTH AND LONGITUDES EAST
C
COMMON/BLOCK1/RCM(90,6),RCZ(95,6),CNSTM(6),CNSTZ(6)
INTEGER*2 NPM(90,6),NPZ(95,6)
COMMON/BLOCK2/NPM,NPZ
REAL*4 P(166),CNMIS(12),CLALO(12),P1TOP8(8)
C
C ALL REGRESSION COEFFICIENTS AND PREDICTOR NUMBERS ARE CONTAINED IN
C IN BLOCK DATA BLKDT1. THERE ARE 90 PREDICTORS AND PREDICTOR
C NUMBERS FOR MERIDIONAL MOTION AND 95 PREDICTORS AND PREDICTOR NUMBERS
C FOR ZONAL MOTION. ((RCM(I,J),J=1,6),I=1,90) AND ((NPM(I,J),J=1,6),I=1,90)
C ARE COEFFICIENTS AND PREDICTOR NUMBERS FOR MERIDIONAL MOTION WHILE
C ((RCZ(I,J),J=1,6),I=1,95) AND ((NPZ(I,J),J=1,6),I=1,95) ARE COEFFICIENTS
C AND PREDICTOR NUMBERS FOR ZONAL MOTION. SUBSCRIPT J REFERS TO TIME WHERE
C J=1=12H.....J=6=72H.
C 6 MERIDIONAL INTERCEPT VALUES ARE GIVEN BY (CNSTM(J),J=1,6) WHILE THE
C 6 ZONAL INTERCEPT VALUES ARE GIVEN BY (CNSTZ(J),J=1,6).
C
C P1 THRU P8 ARE 8 PRIMARY PREDICTORS WHERE...
C   P1 IS INITIAL LATITUDE (DEGS NORTH)
C   P2 IS INITIAL LONGITUDE (DEGS EAST)
C   P3 IS FUNCTION OF JULIAN DAY NUMBER WITH FEB 11 0000UTC
C       SET TO DAY NUMBER 0 AND AUG 12 SET TO MID-YEAR
C   P4 IS MERIDIONAL DISPLACEMENT 00 TO -12H (NMI)
C   P5 IS ZONAL DISPLACEMENT 00 TO -12H (NMI)
C   P6 IS MERIDIONAL DISPLACEMENT 00 TO -24H (NMI)
C   P7 IS ZONAL DISPLACEMENT 00 TO -24H (NMI)
C   P8 IS MAXIMUM WIND (KNOTS)
C
C FUNCTIONS AND SUBPROGRAMS NEEDED BY WPCLPR ARE AS FOLLOWS:
C   DATA NEEDED BY PROGRAM ARE CONTAINED IN BLOCK DATA BLKDT1 AND BLKDT2
C   WPCLPR CALLS SUBROUTINES STHGPR, LL2XYH, PSETUP AND NMI2LL
C       AND UTILIZES FUNCTIONS F1, F2
C   NMI2LL CALLS SUBROUTINE XY2LLH AND UTILIZES FUNCTION F1
C
C SET UP 8 BASIC PREDICTORS.....
C   P1=ALAT00
C   P2=ALON00
C JULIAN DAY NUMBER. GET CONVERSION FACTOR (.008613) SUCH THAT SIN
C OF DAY NUMBER 0 (FEB 11) HAS VALUE NEAR ZERO AND MID-YEAR (AUG 12)
C HAS VALUE NEAR 1.00. NOTE THAT DAY NUMBER IS OFFSET BY 41 DAYS SUCH
C THAT FEB 11 IS DAY NUMBER 0 AND AUG 12 IS MID-YEAR.
C   CONVRT=2.*ACOS(0.)/364.75
C   P3=F2(IDATIM)-41.
C   IF(P3.LT.0.)P3=P3+365.
C   P3=SIN(P3*CONVRT)
C   P8=WIND
C USE AL TAYLOR ROUTINES (SEE NOTE BELOW) FOR CONVERTING LATITUDE/LONGITUDE
C TO DISPLACEMENTS.
C THESE SAME ROUTINES ARE LATER USED FOR CONVERTING DISPLACEMENTS BACK TO
C LATITUDES AND LONGITUDES.....
C NOTE....AL TAYLOR ROUTINES REFER TO SUBROUTINES STHGPR,LL2XYH,XY2LLH

```

```

C (PREDICTORS NUMBER P4 THRU P7)
  CALL STHGPR(P1,F1(P2),360.,1.,0.,0.)
  CALL LL2XYH(ALAT12,F1(ALON12),P5,P4)
  CALL LL2XYH(ALAT24,F1(ALON24),P7,P6)
C ABOVE ALGEBRAIC SIGNS NEED TO BE REVERSED.....
  P4=-P4
  P5=-P5
  P6=-P6
  P7=-P7
C BASIC PREDICTOR SETUP IS COMPLETE. PUT 8 VALUES INTO ARRAY P1TOP8 FOR
C POSSIBLE USE IN CALLING PROGRAM
  P1TOP8(1)=P1
  P1TOP8(2)=P2
  P1TOP8(3)=P3
  P1TOP8(4)=P4
  P1TOP8(5)=P5
  P1TOP8(6)=P6
  P1TOP8(7)=P7
  P1TOP8(8)=P8
C
C PREPARE FORECAST, FIRST, OBTAIN ALL POSSIBLE 3RD ORDER PRODUCTS AND
C CROSS-PRODUCTS OF THE 8 BASIC PREDICTORS AND RETURN THESE IN ARRAY
C (P(L),L=1,166). THERE ARE 164 POSSIBLE COMBINATIONS AND THESE ARE
C GIVEN BY SUBSCRIPTS 3 THROUGH 166. P(1) AND P(2) ARE NOT USED AND HAVE
C BEEN RETURNED AS DUMMY VARIABLES. NOT ALL OF THE 164 POSSIBLE PREDICTORS
C ARE USED IN PROGRAM.
  CALL PSETUP(P1,P2,P3,P4,P5,P6,P7,P8,P)
C OBTAIN FORECAST MERIDIONAL DISPLACEMENTS 12 THRU 72H
  DO 60 J=1,6
C INITIALIZE COMPUTATION WITH INTERCEPT VALUE
  CNMIS(2*J-1)=CNSTM(J)
  DO 50 I=1,90
    K=NPM(I,J)
    CNMIS(2*J-1)=CNMIS(2*J-1)+RCM(I,J)*P(K)
  50 CONTINUE
  60 CONTINUE
C
C OBTAIN FORECAST ZONAL DISPLACEMENTS 12 THRU 72H
C
  DO 80 J=1,6
C INITIALIZE COMPUTATION WITH INTERCEPT VALUE
  CNMIS(2*J)=CNSTZ(J)
  DO 70 I=1,95
    K=NPZ(I,J)
    CNMIS(2*J)=CNMIS(2*J)+RCZ(I,J)*P(K)
  70 CONTINUE
  80 CONTINUE
C CONVERT DISPLACEMENTS TO LATITUDE AND LONGITUDE
  CALL NMI2LL(ALAT00,ALON00,CNMIS,CLALO)
  RETURN
  END

```

```

      FUNCTION F1(ALON)
C  CONVERT FROM E LONGITUDE TO THOSE ACCEPTABLE IN AL TAYLOR ROUTINES
      IF(ALON.GT.180.)F1=360.-ALON
      IF(ALON.LE.180.)F1=-ALON
      RETURN
      END

```

```

      FUNCTION F2(IDATIM)
C  OBTAIN JULIAN DAY NUMBER
C  0000UTC ON 1 JAN IS SET TO DAY NUMBER 0 AND 1800UTC ON 31 DEC IS SET TO
C  DAY NUMBER 364.75.  LEAP YEARS ARE IGNORED.
      CHARACTER*8 ALFA
      WRITE(ALFA,'(I8)')IDATIM
      READ(ALFA,'(4I2)')KYR,MO,KDA,KHR
      MON=MO
      IF(MON.EQ.13)MON=1
      DANBR=3055*(MON+2)/100-(MON+10)/13*2-91+KDA
      F2=DANBR-1.+FLOAT(KHR/6)*0.25
      RETURN
      ENL

```

```

      SUBROUTINE NMI2LL(ALATO,ALONO,CNMIS,CLALO)
C  INCOMING ARGUMENTS:
C    ALATO, ALONO...INITIAL STORM POSTION
C    CNMIS.....FORECAST MERIDIONAL & ZONAL DISPLACEMENTS IN NMI.
C  RETURNED ARGUMENT:
C    CLALO.....FORECASTS IN TERMS OF LAT/LON (SEE NOTE, BELOW)
C
      REAL*4 CNMIS(12),CLALO(12)
      CALL STHGPR(ALATO,F1(ALONO),360.,1.,0.,0.)
      DO 10 I=1,6
      CALL XY2LLH(CNMIS(2*I),CNMIS(2*I-1),CLALO(2*I-1),CLALO(2*I))
C  NOTE: ABOVE SUBROUTINE RETURNS LONGITUDES WEST OF 180 AS NEGATIVE AND
C  EAST OF 180 AS POSITIVE.  CONVERT ALL LONGITUDES TO WHERE EAST IS POSITIVE
C  ZERO TO 180 AND WEST IS POSITIVE 180 TO 360 DEGS.
      IF(CLALO(2*I).GE.0.AND.CLALO(2*I).LT.180.)CLALO(2*I)=360.-
      $CLALO(2*I)
      IF(CLALO(2*I).LT.0.)CLALO(2*I)=-CLALO(2*I)
10  CONTINUE
      RETURN
      END

```

BLOCK DATA BLKDT2

C
C ALBION D. TAYLOR, MARCH 19, 1982
C THE HURRICANE GRID IS BASED ON AN OBLIQUE EQUIDISTANT CYLINDRICAL
C MAP PROJECTION ORIENTED ALONG THE TRACK OF THE HURRICANE.
C
C THE X (OR I) COORDINATE XI OF A POINT REPRESENTS THE DISTANCE
C FROM THAT POINT TO THE GREAT CIRCLE THROUGH THE HURRICANE, IN
C THE DIRECTION OF MOTION OF THE HURRICANE MOTION. POSITIVE VALUES
C REPRESENT DISTANCES TO THE RIGHT OF THE HURRICANE MOTION, NEGATIVE
C VALUES REPRESENT DISTANCES TO THE LEFT.
C THE Y (OR J) COORDINATE OF THE POINT REPRESENTS THE DISTANCE
C ALONG THE GREAT CIRCLE THROUGH THE HURRICANE TO THE PROJECTION
C OF THE POINT ONTO THAT CIRCLE. POSITIVE VALUES REPRESENT
C DISTANCE IN THE DIRECTION OF HURRICANE MOTION, NEGATIVE VALUES
C REPRESENT DISTANCE IN THE OPPOSITE DIRECTION.
C
C SCALE DISTANCES ARE STRICTLY UNIFORM IN THE I-DIRECTION ALWAYS.
C THE SAME SCALE HOLDS IN THE J-DIRECTION ONLY ALONG THE HURRICANE TRACK
C ELSEWHERE, DISTANCES IN THE J-DIRECTION ARE EXAGGERATED BY A FACTOR
C INVERSELY PROPORTIONAL TO THE COSINE OF THE ANGULAR DISTANCE FROM
C THE TRACK. THE SCALE IS CORRECT TO 1 PERCENT WITHIN A DISTANCE OF
C 480 NM OF THE STORM TRACK, 5 PERCENT³ WITHIN 1090 NM, AND
C 10 PERCENT WITHIN 1550 NM.
C
C BIAS VALUES ARE ADDED TO THE XI AND YJ COORDINATES FOR CONVENIENCE
C IN INDEXING.
C
C A PARTICULAR GRID IS SPECIFIED BY THE USER BY MEANS OF A CALL
C TO SUBROUTINE STHGPR (SET HURRICANE GRID PARAMETERS)
C WITH ARGUMENTS (XLATH,XLONH,BEAR,GRIDSZ,XIO,YJO)
C WHERE
C XLATH,XLONH = LATITUDE, LONGITUDE OF THE HURRICANE
C BEAR = BEARING OF THE HURRICANE MOTION
C GRIDSZ = SIZE OF GRID ELEMENTS IN NAUTICAL MILES
C XIO, YJO = OFFSETS IN I AND J COORDINATES (OR I AND J
C COORDINATES OF HURRICANE)
C AND WHERE
C LATITUDES, LONGITUDES AND BEARINGS ARE GIVEN IN DEGREES,
C POSITIVE VALUES ARE NORTH AND WEST, NEGATIVE SOUTH AND EAST,
C BEARINGS ARE GIVEN CLOCKWISE FROM NORTH.
C
C THE CALL TO STHGPR SHOULD BE MADE ONCE ONLY, AND BEFORE REFERENCE
C TO ANY CALL TO LL2XYH OR XY2LLH. IN DEFAULT, THE SYSTEM
C WILL ASSUME A STORM AT LAT, LONG=0.,0., BEARING DUE NORTH,
C WITH A GRIDSIZE OF 120 NAUTICAL MILES AND OFFSETS OF 0.,0. .
C
C TO CONVERT FROM GRID COORDINATES XI AND YJ, USE A CALL TO
C CALL XY2LLH(XI,YJ,XLAT,XLONG)
C
C THE SUBROUTINE WILL RETURN THE LATITUDE AND LONGITUDE CORRESPONDING
C TO THE GIVEN VALUES OF XI AND YJ.
C

C TO CONVERT FROM LATITUDE AND LONGITUDE TO GRID COORDINATES, USE
 C CALL LL2XYH(XLAT,XLONG,XI,YJ)
 C THE SUBROUTINE WILL RETURN THE I-COORDINATE XI AND Y-COORDINATE
 C YJ CORRESPONDING TO THE GIVEN VALUES OF LATITUDE XLAT AND
 C LONGITUDE XLONG.

COMMON /HGRPRM/ A(3,3),RADPDG,RRTHNM,DGRIDH,HGRIDX,HGRIDY
 DATA A /0.,-1.,0., 1.,0.,0., 0.,0.,1./
 DATA RADPDG/1.745 3293 E-2/,RRTHNM /3 440.17/
 DATA DGRIDH/120./
 DATA HGRIDX,HGRIDY/0.,0./
 END

SUBROUTINE PSETUP(P1,P2,P3,P4,P5,P6,P7,P8,P)
 DIMENSION P(166)

C P1 THRU P8 ARE ARE 8 PRIMARY PREDICTORS WHERE...

C P1 IS INITIAL LATITUDE (DEGS)
 C P2 IS INITIAL LONGITUDE (DEGS)
 C P3 IS JULIAN DAY NUMBER FUNCTION (0 TO 1.00)
 C P4 IS MERIDIONAL DISPLACEMENT 00 TO -12H (NMI)
 C P5 IS ZONAL DISPLACEMENT 00 TO -12H (NMI)
 C P6 IS MERIDIONAL DISPLACEMENT 00 TO -24H (NMI)
 C P7 IS ZONAL DISPLACEMENT 00 TO -24H (NMI)
 C P8 IS MAXIMUM WIND (KNOTS)

C P(001 AND 002) ARE DUMMY VARIABLES AND ARE NOT FURTHER USED.

DUMMY=9999.
 P(001)=DUMMY
 P(002)=DUMMY

C P(003)THRU P(166) ARE ALL POSSIBLE PREDICTORS AS OBTAINED FROM CUBIC
 C POLYNOMIAL EXPANSION OF ORIGINAL 8 BASIC PREDICTORS P1 THRU P8.

C
 C LIST THE PREDICTORS.....
 C NOTE: DESIGNATOR IN COLUMN 73 INDICATES WHETHER PREDICTOR WAS USED
 C IN EQUATIONS FOR ZONAL MOTION (Z); IN EQUATIONS FOR MERIDIONAL MOTION (M)
 C OR IN BOTH SETS (B). A BLANK IN COLUMN 73 INDICATES THAT PREDICTOR WAS
 C NOT USED BUT HAS BEEN RETAINED IN PSETUP FOR REFERENCE PURPOSES AND TO
 C FACILITATE INDEXING.

P(003)=P8	Z
P(004)=P8*P8	
P(005)=P8*P8*P8	
P(006)=P7	B
P(007)=P7*P8	
P(008)=P7*P8*P8	
P(009)=P7*P7	
P(010)=P7*P7*P8	M
P(011)=P7*P7*P7	B
P(012)=P6	Z
P(013)=P6*P8	Z
P(014)=P6*P8*P8	
P(015)=P6*P7	M

P(016)=P6*P7*P8	B
P(017)=P6*P7*P7	
P(018)=P6*P6	B
P(019)=P6*P6*P8	
P(020)=P6*P6*P7	B
P(021)=P6*P6*P6	B
P(022)=P5	B
P(023)=P5*P8	
P(024)=P5*P8*P8	
P(025)=P5*P7	Z
P(026)=P5*P7*P8	
P(027)=P5*P7*P7	
P(028)=P5*P6	Z
P(029)=P5*P6*P8	M
P(030)=P5*P6*P7	
P(031)=P5*P6*P6	B
P(032)=P5*P5	B
P(033)=P5*P5*P8	
P(034)=P5*P5*P7	Z
P(035)=P5*P5*P6	Z
P(036)=P5*P5*P5	Z
P(037)=P4	B
P(038)=P4*P8	
P(039)=P4*P8*P8	Z
P(040)=P4*P7	
P(041)=P4*P7*P8	B
P(042)=P4*P7*P7	Z
P(043)=P4*P6	B
P(044)=P4*P6*P8	M
P(045)=P4*P6*P7	B
P(046)=P4*P6*P6	B
P(047)=P4*P5	Z
P(048)=P4*P5*P8	B
P(049)=P4*P5*P7	M
P(050)=P4*P5*P6	
P(051)=P4*P5*P5	M
P(052)=P4*P4	M
P(053)=P4*P4*P8	M
P(054)=P4*P4*P7	B
P(055)=P4*P4*P6	B
P(056)=P4*P4*P5	
P(057)=P4*P4*P4	B
P(058)=P3	M
P(059)=P3*P8	
P(060)=P3*P8*P8	
P(061)=P3*P7	
P(062)=P3*P7*P8	M
P(063)=P3*P7*P7	
P(064)=P3*P6	B
P(065)=P3*P6*P8	B
P(066)=P3*P6*P7	M
P(067)=P3*P6*P6	

P(068)=P3*P5	B
P(069)=P3*P5*P8	B
P(070)=P3*P5*P7	B
P(071)=P3*P5*P6	M
P(072)=P3*P5*P5	Z
P(073)=P3*P4	B
P(074)=P3*P4*P8	B
P(075)=P3*P4*P7	
P(076)=P3*P4*P6	B
P(077)=P3*P4*P5	M
P(078)=P3*P4*P4	Z
P(079)=P3*P3	M
P(080)=P3*P3*P8	Z
P(081)=P3*P3*P7	M
P(082)=P3*P3*P6	M
P(083)=P3*P3*P5	Z
P(084)=P3*P3*P4	B
P(085)=P3*P3*P3	B
P(086)=P2	B
P(087)=P2*P8	
P(088)=P2*P8*P8	Z
P(089)=P2*P7	M
P(090)=P2*P7*P8	
P(091)=P2*P7*P7	
P(092)=P2*P6	M
P(093)=P2*P6*P8	
P(094)=P2*P6*P7	
P(095)=P2*P6*P6	B
P(096)=P2*P5	Z
P(097)=P2*P5*P8	
P(098)=P2*P5*P7	Z
P(099)=P2*P5*P6	
P(100)=P2*P5*P5	M
P(101)=P2*P4	M
P(102)=P2*P4*P8	
P(103)=P2*P4*P7	Z
P(104)=P2*P4*P6	B
P(105)=P2*P4*P5	
P(106)=P2*P4*P4	B
P(107)=P2*P3	B
P(108)=P2*P3*P8	B
P(109)=P2*P3*P7	B
P(110)=P2*P3*P6	B
P(111)=P2*P3*P5	M
P(112)=P2*P3*P4	B
P(113)=P2*P3*P3	B
P(114)=P2*P2	B
P(115)=P2*P2*P8	
P(116)=P2*P2*P7	B
P(117)=P2*P2*P6	B
P(118)=P2*P2*P5	
P(119)=P2*P2*P4	M

P(120)=P2*P2*P3	B
P(121)=P2*P2*P2	Z
P(122)=P1	B
P(123)=P1*P8	Z
P(124)=P1*P8*P8	
P(125)=P1*P7	B
P(126)=P1*P7*P8	Z
P(127)=P1*P7*P7	
P(128)=P1*P6	B
P(129)=P1*P6*P8	B
P(130)=P1*P6*P7	B
P(131)=P1*P6*P6	B
P(132)=P1*P5	B
P(133)=P1*P5*P8	B
P(134)=P1*P5*P7	Z
P(135)=P1*P5*P6	
P(136)=P1*P5*P5	M
P(137)=P1*P4	B
P(138)=P1*P4*P8	B
P(139)=P1*P4*P7	B
P(140)=P1*P4*P6	Z
P(141)=P1*P4*P5	
P(142)=P1*P4*P4	B
P(143)=P1*P3	B
P(144)=P1*P3*P8	
P(145)=P1*P3*P7	B
P(146)=P1*P3*P6	Z
P(147)=P1*P3*P5	
P(148)=P1*P3*P4	B
P(149)=P1*P3*P3	B
P(150)=P1*P2	B
P(151)=P1*P2*P8	
P(152)=P1*P2*P7	
P(153)=P1*P2*P6	B
P(154)=P1*P2*P5	
P(155)=P1*P2*P4	Z
P(156)=P1*P2*P3	Z
P(157)=P1*P2*P2	B
P(158)=P1*P1	B
P(159)=P1*P1*P8	Z
P(160)=P1*P1*P7	M
P(161)=P1*P1*P6	B
P(162)=P1*P1*P5	
P(163)=P1*P1*P4	B
P(164)=P1*P1*P3	Z
P(165)=P1*P1*P2	B
P(166)=P1*P1*P1	B
RETURN	
END	

BLOCK DATA BLKDT1

C
C ENTER ALL CONSTANTS NEEDED BY WPCLPR PROGRAM.....
C

```

INTEGER*2 N12M(90),N24M(90),N36M(90),N48M(90),N60M(90),N72M(90)
INTEGER*2 N12Z(95),N24Z(95),N36Z(95),N48Z(95),N60Z(95),N72Z(95)
REAL*4 R12M(90),R24M(90),R36M(90),R48M(90),R60M(90),R72M(90)
REAL*4 R12Z(95),R24Z(95),R36Z(95),R48Z(95),R60Z(95),R72Z(95)
COMMON/BLOCK1/RCM(90,6),RCZ(95,6),CNSTM(6),CNSTZ(6)
INTEGER*2 NPM(90,6),NPZ(95,6)
COMMON/BLOCK2/NPM,NPZ

```

C
EQUIVALENCE
\$(N12M(1),NPM(1,1)),(N24M(1),NPM(1,2)),(N36M(1),NPM(1,3))
EQUIVALENCE
\$(N48M(1),NPM(1,4)),(N60M(1),NPM(1,5)),(N72M(1),NPM(1,6))
EQUIVALENCE
\$(N12Z(1),NPZ(1,1)),(N24Z(1),NPZ(1,2)),(N36Z(1),NPZ(1,3))
EQUIVALENCE
\$(N48Z(1),NPZ(1,4)),(N60Z(1),NPZ(1,5)),(N72Z(1),NPZ(1,6))

C
EQUIVALENCE
\$(R12M(1),RCM(1,1)),(R24M(1),RCM(1,2)),(R36M(1),RCM(1,3))
EQUIVALENCE
\$(R48M(1),RCM(1,4)),(R60M(1),RCM(1,5)),(R72M(1),RCM(1,6))
EQUIVALENCE
\$(R12Z(1),RCZ(1,1)),(R24Z(1),RCZ(1,2)),(R36Z(1),RCZ(1,3))
EQUIVALENCE
\$(R48Z(1),RCZ(1,4)),(R60Z(1),RCZ(1,5)),(R72Z(1),RCZ(1,6))

C
C 12HR MERIDIONAL REGRESSION COEFFICIENTS
DATA R12M/

```

A .3243071E-1, .8344170E-1, .3097537E-5, .1585081E-4, -.5781467E+0,
B .5559386E-1, -.1366367E-2, -.3860944E-3, -.1971581E-1, -.1506403E+0,
C -.4094524E-4, -.5283375E-5, -.3027484E+0, .8434259E-5, -.3899679E-4,
D .9574963E-7, .4653325E+0, .1591545E-4, .7693003E-2, -.1005234E-5,
E .3358553E-7, .1633963E-3, .1816813E-1, -.6719710E-4, -.1759287E-4,
F -.7372505E-6, -.1096292E-3, .6955126E-2, .5218342E-4, .5895122E+0,
G .2061950E-4, -.2190146E-3, .5322326E-4, -.2373855E-4, .4469749E-4,
H -.2265381E-4, .1979948E-5, -.5109265E-2, -.2950181E-3, .6109930E+1,
I .7605872E+1, -.4546854E-4, .1600313E-5, -.2928901E-2, .4102941E+1,
J .1390362E-3, -.3042169E-6, .2936898E-2, .2463492E-4, -.5564410E-5,
K -.1063433E-1, .2013024E-4, .1141800E-3, -.3022033E-2, .8813960E-4,
L -.5440627E+1, .3820794E+3, -.8052462E+2, -.1642693E-1, .1319590E-2,
M .3117979E-3, -.5988197E+3, -.1305264E-2, .5542873E+1, .4542397E-2,
N .2795997E-1, -.1545122E+0, -.9023645E-2, -.5600628E-4, -.1015321E+1,
O .8042760E-3, -.9450367E-4, -.4567757E+1, .3214121E-1, -.1547069E-1,
P .2040100E+1, -.2301845E-2, .4422556E-4, -.5294287E-2, -.3743809E-3,
Q -.2507454E-5, -.3437747E-2, .1066433E-3, -.1318755E-3, .4227765E-6,
R .1076038E-3, .1793193E-3, .2274033E-5, -.2935162E-2, .5331651E-7/

```

C

C 12HR MERIDIONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N12M/

A	037,	022,	021,	053,	006,
B	137,	163,	077,	120,	082,
C	057,	044,	150,	100,	136,
D	011,	158,	142,	043,	049,
E	031,	015,	101,	104,	116,
F	020,	119,	089,	132,	068,
G	130,	066,	055,	046,	117,
H	139,	045,	092,	071,	107,
I	122,	153,	131,	111,	086,
J	070,	010,	065,	048,	016,
K	125,	095,	076,	166,	160,
L	149,	079,	085,	114,	157,
M	161,	058,	165,	143,	145,
N	148,	084,	128,	133,	113,
O	069,	129,	073,	112,	110,
P	064,	018,	106,	052,	109,
Q	041,	074,	138,	032,	051,
R	108,	062,	029,	081,	054/

C

C 24HR MERIDIONAL REGRESSION COEFFICIENTS

DATA R24M/

A .3153820E+0, .2997032E+0, .1041448E-4, .5041134E-4, -.1156390E+1,
 B .5317333E-1, -.208431E-2, .3042450E-4, -.8799762E-4, .1022893E+2,
 C .6685339E+0, -.1132432E-3, -.9044307E-4, .7902439E-3, .1087582E-5,
 D .1859850E-6, -.1018892E-2, -.3072454E-5, -.2157618E-4, .7834254E-3,
 E .3795866E+1, -.7374839E-4, .2412219E-1, -.4092464E-1, -.1858413E-3,
 F -.2764014E-4, -.3711128E+0, .1323014E-1, .2087213E-3, .7945657E-4,
 G -.2079803E-5, -.7822717E-5, .5451679E-4, -.5515313E-5, .1539684E-3,
 H -.7315785E-4, .1385716E+1, -.2411789E+0, -.7403991E-2, .2715513E-1,
 I -.8068998E-2, .7467210E-1, -.2263752E+1, .4163469E-4, .9148016E-5,
 J .7552782E-1, -.4364474E-3, .4935954E-3, -.7837036E-2, -.1643844E-3,
 K -.5313780E-2, .2868564E-4, -.1810828E+3, .1136112E+4, -.1415626E+4,
 L -.2540406E-1, -.3354503E+1, -.9715013E-2, .9202192E-4, -.7580452E+1,
 M -.7241050E-2, .1560430E+1, .2163080E-2, -.2943305E-1, -.2664132E+2,
 N .3334467E+2, -.4484441E-1, .1021904E+2, -.1022645E-2, .1614939E-2,
 O -.1983720E+2, -.7248729E-4, .2943276E-2, -.9322744E-3, .2136197E-1,
 P .5946692E-4, -.2623588E-5, .6422937E-3, .7898051E-4, -.4097134E-3,
 Q .4658792E-6, -.6674667E-5, -.9276444E-5, -.3350714E-3, .8076304E-4,
 R -.9702706E-2, .7907680E-2, -.1429927E-1, -.1911111E-4, -.2009685E-3/

C

C 24HR MERIDIONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N24M/

A	037,	022,	021,	053,	006,
B	137,	163,	100,	136,	107,
C	082,	057,	153,	077,	049,
D	011,	066,	020,	044,	015,
E	064,	139,	101,	110,	119,
F	116,	150,	089,	161,	160,
G	010,	016,	048,	051,	055,

H	046,	068,	081,	111,	145,
I	132,	148,	084,	130,	045,
J	112,	071,	108,	018,	104,
K	165,	131,	085,	079,	058,
L	120,	113,	166,	117,	073,
M	092,	158,	157,	125,	149,
N	143,	114,	086,	032,	128,
O	122,	133,	069,	062,	043,
P	095,	054,	138,	070,	076,
Q	031,	029,	041,	129,	106,
R	052,	065,	074,	142,	109/

C

C 36HR MERIDIONAL REGRESSION COEFFICIENTS

DATA R36M/

A .5950992E+0, .5950849E+0, .1579387E-4, .1456014E-2, .3207405E-1,
 B-.7676163E-3, -.5470162E-2, .3885264E-4, .2219862E+2, -.5390780E-1,
 C-.1517608E-3, -.2491167E-2, -.1428840E-3, .4585012E-6, -.3401252E-4,
 D-.1972049E-4, -.5636768E-5, -.1414913E-4, -.1650207E-4, .2669300E-1,
 E-.3509095E-2, -.7492083E+1, -.1600104E-3, .1732787E-3, -.4668803E-1,
 F-.3349135E+4, -.2492286E+1, .5827907E-4, -.2699760E-5, -.4194588E+1,
 G .1183714E+0, -.6774910E+1, .2363143E+4, -.2766386E+3, -.4127603E-5,
 H-.6793531E-1, .6692806E-4, .2140080E-3, -.1051408E-3, .1574291E-1,
 I .1702305E-1, .3132313E+1, -.4267311E-3, -.1081547E-3, .9454913E-1,
 J .2723925E-4, .4721174E-4, .5315742E-5, .2633784E-2, .2876436E+1,
 K-.6931119E+2, -.1433271E-1, -.6981828E+2, .9248463E+2, -.1159544E-1,
 L-.1766660E-3, .8383029E-4, .1154778E+1, -.2878250E-3, -.4039820E-1,
 M .6119043E-1, -.5965958E+0, -.9011731E-4, -.2723274E-2, .1115074E-2,
 N .7571446E-4, -.1824643E-1, .1490073E-2, -.1465571E-4, .7776189E-2,
 O .1428073E+1, -.2494387E-2, .1327341E+2, -.5822539E-2, .3420847E-2,
 P-.4875488E-2, -.1737409E-3, .1659009E-1, -.2884431E-1, .3345077E-1,
 Q-.2379260E-3, -.2867373E+0, .1725656E-4, .3078079E-4, -.2416038E-3,
 R-.1258763E-3, -.1207252E-2, .1942326E-5, .8619620E-5, -.3816745E-4/

C

C 36HR MERIDIONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N36M/

A	037,	022,	021,	138,	089,
B	129,	018,	048,	107,	110,
C	139,	032,	136,	011,	044,
D	016,	020,	051,	131,	137,
E	163,	113,	057,	142,	120,
F	058,	006,	100,	010,	084,
G	148,	073,	079,	085,	031,
H	114,	053,	055,	046,	043,
I	101,	064,	071,	104,	112,
J	045,	095,	049,	157,	158,
K	149,	166,	122,	143,	165,
L	133,	130,	068,	070,	125,
M	145,	081,	116,	066,	015,
N	117,	132,	108,	054,	069,
O	082,	062,	086,	111,	077,
P	052,	119,	065,	074,	128,
Q	160,	150,	029,	153,	109,

R 076, 092, 041, 106, 161/

C

C 48HR MERIDIONAL REGRESSION COEFFICIENTS

DATA R48M/

A .3937869E+1, .2704789E-2, .2041786E-4, -.5296992E-5, .3595185E-5,
 B-.1586901E+0, -.8895839E-2, .1017758E+1, -.1341447E-1, .4795113E+2,
 C .1117224E-3, .2237810E-5, -.4391966E-4, -.5562625E+3, .1197306E-1,
 D-.1089932E+0, -.6775073E+4, .4272758E+4, -.3806239E-1, -.3994735E-2,
 E-.4841974E-1, -.2401614E-3, .3658880E+1, .3839169E-4, .7278352E-4,
 F-.1407710E-4, .3700307E-6, -.1041093E-3, -.6224410E+0, -.2864941E-1,
 G .1032796E+0, -.1316307E-3, .2266372E-3, -.4527995E-6, .1751338E-2,
 H .6244212E-4, .8839133E-1, -.1296256E-2, -.4048634E-1, -.1973882E-3,
 I .2567629E-3, .4855618E-5, -.3332841E-3, .2033777E+0, -.6754591E-1,
 J-.1992392E-3, -.1316714E+2, -.7344471E-1, .3646203E-2, -.1834054E-5,
 K .1025236E-3, -.3341298E-4, .2875189E-1, -.5913152E-3, -.2675888E-5,
 L-.1456183E-3, .4367509E-1, -.3902138E+1, .6231806E-1, -.3691021E-2,
 M-.3008487E-3, -.3720047E-4, .9663910E+1, -.3045679E-2, -.1404164E+3,
 N .4988254E+1, -.2738102E-1, -.1190210E+3, .1629256E+3, -.1440433E-2,
 O .3320168E-2, -.2063279E-1, .3450813E-2, .2031545E-2, .1344573E+0,
 P-.5192478E-1, .1217591E+0, -.8695283E+1, -.4237666E+1, .6357585E-4,
 Q-.2035649E-1, .1203182E-1, -.2478962E-3, -.3098815E-2, -.9350809E-5,
 R .2607693E-4, -.2601418E-2, .1757823E-3, .1826342E-5, -.1595340E+0/

C

C 48HR MERIDIONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N48M/

A	037,	138,	021,	048,	041,
B	022,	109,	082,	018,	107,
C	095,	044,	131,	085,	111,
D	120,	058,	079,	137,	163,
E	125,	160,	064,	153,	100,
F	051,	011,	136,	081,	101,
G	128,	046,	142,	054,	077,
H	117,	145,	070,	132,	057,
I	055,	053,	104,	068,	110,
J	116,	113,	114,	108,	010,
K	130,	016,	065,	076,	031,
L	139,	043,	006,	089,	032,
M	161,	119,	086,	066,	122,
N	158,	166,	149,	143,	129,
O	157,	165,	092,	015,	148,
P	074,	112,	073,	084,	029,
Q	052,	069,	133,	062,	020,
R	045,	071,	106,	049,	150/

C

C 60HR MERIDIONAL REGRESSION COEFFICIENTS

DATA R60M/

A .3203984E-2, .3214552E+1, .2423918E-4, -.7785958E+0, -.1492266E-1,
 B .1039869E+1, -.3005961E-1, .2310288E-3, -.2280654E+0, .5501085E+1,
 C .2990582E+0, -.9901556E-2, -.2098349E-1, -.1705836E-3, -.6350436E-3,
 D .7693167E-1, .5199465E-3, .6955174E-2, .8453595E-3, .1846887E-1,
 E-.5268668E-3, -.8680647E-1, -.5915611E+0, -.7375913E+0, .7631609E-4,
 F-.2451390E-2, .9023706E+2, -.1148612E+5, -.9789110E+3, .6385988E+4,

G-.2257996E-2,-.2955700E-3, .3620264E-3, .1243156E+0, .2286977E-2,
H-.2588321E-3,-.2050898E-4, .1036300E+0,-.3067020E-3,-.1872121E+2,
I-.7393541E-1,-.1216293E+2, .2388042E-1,-.2839831E-4, .4525014E-4,
J-.2995554E-4, .4003014E-6, .1001026E+0,-.5637052E-2, -.4621421E-4,
K-.4773916E-4,-.9231204E-3,-.1052938E+0,-.4006194E-6,-.4930203E+1,
L-.8322347E-1,-.1939114E-2,-.7524058E-4, .4381766E-2,-.6379662E-1,
M .3660681E-1,-.1722834E-4, .5012191E-4, .9200552E-4, .1084389E-3,
N-.4450581E-2, .3444209E-5, .9086277E-1,-.5094324E+1,-.2391547E-2,
O-.1673092E+3, .2319061E+3,-.1755640E+3, .7775852E+1,-.5396487E-1,
P-.1063858E-1,-.1351081E-3, .6457442E-2,-.2869241E-1, .1514071E+0,
Q .2197347E-3,-.2746503E-2,-.3307905E-2,-.7339347E+0, .3619938E-4,
R .1011086E-3,-.2434152E-4, .4017977E+1, .6680801E-6,-.1003097E-1/

C

C 60HR MERIDIONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N60M/

A	138,	037,	021,	022,	109,
B	082,	018,	095,	120,	064,
C	137,	163,	132,	046,	153,
D	148,	160,	108,	106,	069,
E	133,	125,	081,	068,	100,
F	070,	107,	058,	085,	079,
G	062,	057,	055,	043,	161,
H	119,	051,	128,	116,	113,
I	114,	073,	111,	054,	041,
J	053,	011,	145,	077,	048,
K	139,	104,	052,	010,	084,
L	110,	129,	016,	015,	074,
M	065,	020,	045,	130,	029,
N	071,	049,	089,	006,	032,
O	149,	143,	122,	158,	166,
P	092,	136,	157,	165,	112,
Q	117,	066,	076,	150,	044,
R	142,	131,	086,	031,	101/

C

C 72HR MERIDIONAL REGRESSION COEFFICIENTS

DATA R72M/

A .3488563E-2, .3701970E+1,-.9708924E+0, .4008871E-2,-.1293923E-1,
B-.7090221E-1,-.3742748E-3, .1105047E-1,-.4330272E-3,-.8182453E-1,
C .1095407E-1, .5478795E+0,-.1447806E+0,-.9794039E-1, .2239485E+0,
D-.1661157E-2, .4048455E-1,-.1006988E-2, .1850597E+0,-.2174177E+1,
E-.8687648E-3,-.6220469E-2, .1288180E+3, .1852817E-2, .6048402E-1,
F-.1280221E+4, .8505950E+4,-.1602371E+5,-.3252233E+0,-.1609533E-1,
G .1029853E+2,-.3748759E-4, .9792199E-4, .4511779E-3,-.2162620E-3,
H .2205770E-3,-.1151997E-1, .3387292E-4, .2349918E-1,-.2588824E+2,
I-.8928016E-1, .6423026E-2,-.3158766E-6,-.5107375E-2, .5468760E-3,
J .8253090E-2,-.2154140E+3, .2989108E+3,-.2354096E+3,-.3862253E-1,
K-.2662852E-4, .1051974E+2,-.8225405E-1,-.3635149E-1,-.7247429E+1,
L .3891779E-3,-.8137807E-5, .5224281E-4,-.2422649E-2,-.5477626E+0,
M-.8151363E-4,-.7235619E-4,-.1810511E-3, .1377748E+1,-.3594793E-4,
N-.2512651E-2, .4714961E-1,-.9353195E-1,-.2171966E+2, .7037701E-4,
O .6227463E-6,-.9167926E+0,-.1582993E-3, .1218130E+0,-.1326393E-1,
P .3112528E-4, .2236540E-3,-.4258522E-2, .7624116E-5, .3593528E-5,

Q .7404723E-3,-.2894253E-1,-.4697331E-3, .1298922E+0,-.1438011E+1,
R .8325552E-3,-.3026344E-5, .7633657E+0, .1031796E-2, .1344312E-4/

C

C 72HR MERIDIONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS
DATA N72M/

A	138,	037,	022,	161,	109,
B	074,	057,	108,	119,	125,
C	101,	137,	148,	052,	128,
D	153,	069,	133,	112,	082,
E	104,	062,	107,	160,	145,
F	085,	079,	058,	120,	132,
G	064,	020,	045,	055,	046,
H	095,	163,	021,	111,	113,
I	114,	015,	041,	066,	142,
J	157,	149,	143,	122,	092,
K	130,	158,	166,	165,	006,
L	117,	049,	100,	070,	081,
M	053,	054,	136,	086,	016,
N	129,	065,	110,	073,	044,
O	011,	150,	131,	043,	077,
P	029,	139,	076,	031,	010,
Q	106,	018,	116,	089,	068,
R	032,	051,	084,	071,	048/

C

C 12 THROUGH 72HR MERIDIONAL INTERCEPT VALUES

DATA CNSTM/

\$-.17755E+3,-.30486E+3,-.73569E+1,0.99119E+3,0.22569E+4,0.33789E+4/

C

C 12HR ZONAL REGRESSION COEFFICIENTS

DATA R12Z/

A .9006323E+0, .2636530E+0, .2715837E-1,-.5035076E-5,-.4328413E-2,
B-.1534302E+2,-.1670920E+2, .1099782E+2,-.5405415E-6,-.1375598E-4,
C .2705107E-5,-.2260919E-5,-.3761767E-1,-.7464690E-3,-.1119880E+1,
D-.3803272E-1, .1807599E-3, .2247620E+0,-.4954901E-3, .1190615E+0,
E .4359363E-3,-.1709496E-5, .9452690E-6,-.4804899E-5, .1946948E-3,
F-.1015711E-4, .9425162E-1, .4855394E-2, .5402028E-2, .4124690E-6,
G-.8267158E-4, .3497515E-2,-.1692273E-2,-.3936120E-5, .2677127E-5,
H .3451866E-1, .2196571E-4, .3035431E+0, .1088666E+3,-.4243606E-2,
I .1757287E+0,-.2453161E-4, .2089448E-4, .1354813E-2, .6455932E-6,
J-.2679381E-2,-.5688711E+0,-.1587587E+1, .3006070E-2,-.1166579E-4,
K .1542880E-2,-.1347129E-2,-.2322664E-4, .3315306E-3, .8377724E-4,
L .2618641E+0, .5893461E+0,-.5805363E+0,-.7381478E-4, .1035842E-1,
M-.1843956E-4, .2631674E-4,-.1101112E-1,-.2608365E-6,-.8394727E-5,
N-.4267192E-3, .2838702E-2,-.4894629E-5, .7210605E-3, .5548951E-3,
O-.5022169E-1,-.5837255E+0, .3080611E-2, .3913114E-3,-.8009970E-3,
P .2737874E-1,-.1580960E-5, .3713773E-5, .1506041E-2,-.1662541E-3,
Q .2841699E-2, .4002706E-5, .1652561E+2,-.1215014E+0, .2955007E-3,
R-.1946682E-2, .2823429E-4,-.2398549E-2,-.1147224E-4,-.3934242E-4,
S-.5558193E-3, .1033347E-3, .2654649E-1,-.3655712E-4,-.0649221E-9/

C

C 12HR ZONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N12Z/

A	022,	012,	006,	036,	110,
B	122,	149,	143,	020,	048,
C	034,	041,	128,	161,	084,
D	148,	133,	083,	157,	150,
E	025,	035,	021,	098,	070,
F	103,	137,	047,	156,	031,
G	126,	145,	028,	054,	045,
H	146,	130,	158,	085,	166,
I	164,	139,	131,	018,	042,
J	125,	068,	107,	120,	046,
K	032,	072,	106,	153,	142,
L	073,	113,	037,	163,	112,
M	057,	055,	074,	039,	117,
N	155,	096,	116,	078,	069,
O	080,	003,	108,	138,	159,
P	123,	134,	016,	013,	129,
Q	065,	088,	086,	114,	121,
R	132,	104,	043,	095,	140,
S	076,	109,	064,	165,	011/

C

C 24HR ZONAL REGRESSION COEFFICIENTS

DATA R24Z/

A .2211812E+1, .2502268E-2, .1611160E+0, -.2591848E+2, .1432364E-1,
 B-.9113922E-5, .6079792E-2, -.1401346E+1, .1332991E-4, .7052931E-2,
 C-.2593970E-3, .2451430E-5, .4769637E-2, -.4306809E-4, .3054334E-5,
 D .1000287E-1, -.5108636E+2, -.4080394E-3, .6407317E-3, .2993321E-5,
 E-.4237494E-4, .1457416E-4, .6738167E+0, -.2469574E-3, -.9215541E-5,
 F-.3256473E+1, .3334723E+0, -.1323649E-2, .1331422E+0, .2425374E-3,
 G-.1390987E-4, -.6551803E-3, .2598725E+1, .1060368E+1, .8170489E-4,
 H-.2564629E-5, -.1473495E-4, -.1176913E-1, -.3080450E-3, .3336047E-2,
 I .3844014E-3, .3177928E+0, .2574205E+3, -.5082541E-4, -.1202910E-3,
 J-.1963487E+1, .3509171E-2, .9577802E-5, .1449019E-4, -.5303399E+1,
 K .3860714E+2, -.1294830E-4, .2337055E+2, -.1995571E-2, -.1613782E-1,
 L-.1645496E+0, .4070771E-2, .4351837E-2, -.1486245E-2, -.2513986E-5,
 M .4734735E-6, -.1403628E-5, -.2059850E-4, .3792110E-3, -.1089386E-3,
 N .3298255E-1, -.8059559E-3, -.2020980E+0, -.2919412E-1, .9324504E-3,
 O .1088125E-4, .5408395E-1, -.4968320E-2, -.1688111E-2, -.2543072E-3,
 P .1081524E-3, .6010513E-6, -.6003507E-6, -.2923749E-4, .4013145E-4,
 Q .1901449E+0, .9298589E-3, -.2121820E+1, .1362282E+1, -.1177176E+0,
 R-.1236508E-2, .1540775E-1, -.2104262E-1, .1784882E-1, -.4841833E-2,
 S .6806184E-2, .5477094E+0, -.1416732E+0, .7317505E-1, .3173007E-6/

C

C 24HR ZONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N24Z/

A	022,	013,	006,	122,	156,
B	036,	065,	003,	045,	120,
C	129,	021,	018,	095,	034,
D	108,	149,	157,	032,	134,
E	041,	048,	083,	072,	117,
F	084,	137,	161,	146,	133,
G	054,	165,	113,	158,	131,
H	031,	098,	166,	109,	025,

I	121,	164,	085,	139,	126,
J	068,	069,	088,	130,	107,
K	143,	116,	086,	159,	110,
L	114,	096,	047,	028,	103,
M	011,	020,	046,	142,	106,
N	112,	163,	128,	074,	138,
O	016,	123,	043,	070,	140,
P	104,	042,	035,	057,	055,
Q	073,	153,	037,	012,	148,
R	155,	145,	125,	132,	076,
S	078,	064,	080,	150,	039/

C

C 36HR ZONAL REGRESSION COEFFICIENTS

DATA R36Z/

A .3727141E+1, -.7587179E-3, .2658744E+0, -.1064598E-3, .1630746E-1,
 B .3809214E-2, .1670243E+1, .1278819E+0, -.2416541E+1, .1913527E-1,
 C .2704694E-5, -.1120205E-4, -.1614327E-2, .2591370E-3, -.1047507E+3,
 D .1332363E-2, .9398222E-6, .3414695E-5, .3046316E-2, -.2506951E-4,
 E -.4670072E+1, .2852724E+0, -.2901490E-2, -.5540189E-2, .3602891E-4,
 F .1995485E+1, .4871011E+3, .2478877E+0, -.1650441E-1, .5286175E-5,
 G -.2476632E-2, .5060762E-2, -.9612819E-4, -.1830817E+0, -.9639716E+1,
 H .5297878E-3, .3464923E-2, -.8071997E-4, .5602714E-4, -.2543369E-4,
 I .3584953E-3, .1382637E-2, -.5244200E+0, -.2599436E-4, .1835390E-4,
 J .6094095E-2, .6309593E-6, -.7754817E-5, .2240740E-4, .3052519E+2,
 K .3810123E-2, -.2447143E-2, -.3723550E+1, .1524773E+1, .4064334E-4,
 L .7461656E+2, .5375246E+1, .3403604E+0, .1128191E-3, -.4142378E-4,
 M -.1096141E-2, -.2166006E-4, -.3244383E-3, -.1244384E-2, .2974604E-1,
 N -.3203653E-1, -.3656643E-3, .3284611E-3, -.7873988E-4, -.1792683E-2,
 O .1730848E-1, -.5773084E-1, .2119286E-2, .2361585E-1, -.1913189E-5,
 P .1293529E-4, -.1816199E+0, -.8990942E+0, .8328797E-1, .4267458E-3,
 Q -.1628386E-3, -.1352078E-1, .2006030E-1, .2214782E+1, .5751397E-3,
 R -.1934013E+0, -.2339948E+1, -.2175043E-2, -.2371471E+1, .3393036E+1,
 S .6895464E-2, -.7135277E-3, .2778157E-6, .6514657E-3, -.3385307E-5/

C

C 36HR ZONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N36Z/

A	022,	129,	006,	139,	065,
B	013,	122,	156,	003,	108,
C	021,	036,	043,	104,	149,
D	157,	011,	035,	047,	117,
E	084,	137,	161,	110,	130,
F	158,	085,	146,	166,	103,
G	070,	025,	057,	128,	107,
H	109,	069,	041,	048,	098,
I	121,	142,	150,	116,	088,
J	018,	034,	031,	045,	086,
K	096,	159,	068,	083,	134,
L	143,	113,	164,	055,	046,
M	163,	054,	106,	140,	132,
N	125,	155,	131,	095,	072,
O	145,	074,	138,	112,	020,
P	016,	114,	080,	123,	133,

Q	126,	076,	078,	012,	153,
R	148,	037,	165,	064,	073,
S	120,	028,	042,	032,	039/

C

C 48HR ZONAL REGRESSION COEFFICIENTS

DATA R48Z/

A	.4461890E+1,-.1317868E-2,-.7756542E-1,-.2763940E+1, .1010894E+0,
B	.3552770E-3,-.1131051E-2,-.2969235E-5, .1778276E+1, .2697765E-1,
C	.1864808E-5, .3829534E-1, .2664764E+2,-.1670381E+3, .1257320E+3,
D	-.3611783E-4, .2327583E-1,-.4939107E-2, .1812029E+0, .3345573E+1,
E	.8995103E+1,-.1514329E+2,-.6056705E-4,-.7867934E-5, .8154577E-3,
F	.9369705E-4,-.5978556E+1,-.1621266E+0,-.3687867E-3,-.5121806E-2,
G	.1744368E-5,-.1546340E+1,-.6412392E-5, .1418515E-3,-.6517249E-4,
H	-.3501834E-1, .3596652E-1,-.3548717E+1,-.2720283E-3,-.1781469E-2,
I	.4078705E-3, .2880435E+0, .6823913E+3, .4768583E-1, .3167891E-2,
J	-.2810874E-3, .3799080E-5,-.4648817E-2, .6123276E-2,-.2612873E-4,
K	-.4936589E+1, .1889149E+1, .1788154E-4,-.1734991E-2,-.8497788E+1,
L	.5695087E-1, .2262154E-3, .2080020E-4, .7392030E-4,-.1816474E-1,
M	.4006617E-5, .6725874E+0,-.1372697E-3, .1686805E-3, .3139948E-2,
N	-.2296015E+0, .1188443E+2,-.1883356E-4,-.5851002E-5, .3567081E-1,
O	-.9073536E-3,-.1360315E-2,-.8653859E-1, .3236842E-2, .1021488E-4,
P	.6974207E-3, .3197120E-4,-.5162931E-5,-.9823154E-3,-.3572130E-1,
Q	-.1283591E+1, .3775808E+0, .3752357E+2, .3439863E-2,-.2016348E+0,
R	.6570792E-2, .1875953E-2, .2744629E-2, .6777080E-3,-.2940123E-4,
S	.7908021E-5,-.1325029E+0, .3122459E-6,-.2446544E-3,-.5342702E-4/

C

C 48HR ZONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N48Z/

A	022,	129,	125,	080,	123,
B	121,	109,	020,	012,	065,
C	021,	110,	122,	149,	143,
D	116,	043,	161,	128,	158,
E	113,	107,	041,	036,	133,
F	130,	084,	148,	106,	165,
G	011,	037,	048,	104,	046,
H	076,	108,	003,	126,	159,
I	131,	146,	085,	078,	155,
J	139,	042,	070,	025,	098,
K	068,	083,	103,	153,	064,
L	145,	120,	088,	134,	166,
M	054,	006,	057,	055,	013,
N	137,	073,	117,	031,	132,
O	140,	072,	074,	138,	016,
P	028,	039,	034,	163,	112,
Q	150,	156,	086,	157,	114,
R	096,	069,	047,	142,	095,
S	045,	164,	035,	018,	032/

C

C 60HR ZONAL REGRESSION COEFFICIENTS

DATA R60Z/

A	.2069224E+1,-.1103176E-2,-.2064642E+0,-.4983683E+1, .1536261E+0,
B	.3199196E+2,-.5460705E-2, .1255320E-5, .1520694E+0,-.6864076E+0,

C-.2703545E-3,-.1377396E+2,.1772634E+1,.1634603E-2,-.2168856E+3,
 D .2124165E+3,-.5698305E+1,.1273810E+2,-.7063864E-2,.9227938E-2,
 E-.2284709E-2,.1370015E+2,-.2228472E+2,.6789817E+1,-.8620483E-2,
 F .1313456E-2,.5443990E-5,-.2303747E-2,-.3724907E-4,.7411583E-4,
 G .1284778E+0,-.1373733E-1,.2003673E-1,.1401725E+0,.2426811E+1,
 H-.8314399E-2,.3955336E-2,.1900598E-4,.5113706E-1,-.3800525E+1,
 I .6040041E+3,-.9981981E+1,.1325930E-3,.3052361E-5,.2668688E-3,
 J .2324372E-5,.7160340E-2,.1391306E-2,-.3548335E-4,-.1137031E-2,
 K-.6057272E-2,-.1427741E-1,-.9021798E-4,-.6861619E-3,.4349863E-4,
 L .2274543E-3,-.4777696E+1,-.5904185E-4,-.8227909E-1,.3152315E-1,
 M .2462513E-2,.5017710E+0,-.1096284E-1,-.1977392E-1,.7290724E-2,
 N-.2129486E-4,.3000092E+1,-.1765608E-4,-.2304361E+1,.6947934E+0,
 O .3114901E-1,-.3943682E+1,.4459878E-3,-.1227436E-3,-.6873362E-5,
 P .2243630E-4,-.1889643E+1,.5570258E-2,-.1523624E+0,.1353138E+0,
 Q .1710850E-2,.6295090E-3,-.8884525E-6,.3560092E-2,-.8806022E-4,
 R-.2366248E-3,.4754374E-2,.1822556E-4,-.1445557E-2,.2511212E-1,
 S .1707720E-5,.2121491E-3,-.2604274E-4,-.1148665E-5,-.7936591E-6/

C

C 60HR ZONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N60Z/

A	022,	129,	125,	080,	123,
B	086,	109,	020,	137,	148,
C	057,	122,	083,	155,	149,
D	143,	068,	073,	112,	163,
E	159,	113,	107,	158,	013,
F	142,	042,	070,	036,	134,
G	132,	166,	096,	145,	006,
H	072,	025,	034,	108,	003,
I	085,	064,	039,	021,	055,
J	054,	078,	018,	095,	140,
K	120,	165,	046,	139,	103,
L	130,	084,	116,	074,	065,
M	138,	146,	161,	076,	069,
N	016,	012,	098,	164,	156,
O	043,	037,	131,	106,	031,
P	041,	150,	157,	114,	128,
Q	028,	133,	011,	032,	048,
R	126,	047,	117,	153,	110,
S	035,	121,	104,	088,	045/

C

C 72HR ZONAL REGRESSION COEFFICIENTS

DATA R72Z/

A .2395405E-1,-.7806209E-3,-.1842410E+0,-.8005585E+1,.1556506E+0,
 B-.6327140E+1,.2253897E+2,.6253895E-1,-.1755240E-1,.1005779E+0,
 C .3755404E-3,.2901980E-2,.3114197E+3,-.7669319E+2,-.2248932E+3,
 D .2924744E+3,-.2680036E+2,.1069149E+2,.1748429E+2,-.2428297E-1,
 E .2038599E+1,.1848174E-1,.3960758E-1,-.1984342E-4,-.2583482E-2,
 F .1510835E-1,.1105277E+1,-.1305345E+1,.4382738E-1,-.1063787E+1,
 G .8457217E-5,-.3720603E+1,-.3133037E+1,.7266772E-1,-.2743943E-3,
 H-.4373971E-2,-.2921431E-2,-.1547001E-4,.4130158E-2,.3275995E+1,
 I .3118712E-3,-.8542968E-1,.7297505E-2,-.1557678E-1,-.4920905E-4,
 J .3283889E+1,.1532788E+0,-.6655574E+1,-.1290537E-1,.6191022E+0,

K-.3637749E+1,-.3909813E-3,-.1151147E-3, .1544773E-1,-.7489980E-3,
L-.2239653E-3, .1315061E-2,-.2339805E-1,-.2173305E-1,-.1989875E-3,
M .8305500E-1,-.1606589E-1,-.7300878E-1,-.6183341E-4,-.8706669E-3,
N .9752020E-4, .3106925E-3, .2559696E-4, .6615661E-2, .1022580E-2,
O-.2911379E-2, .8294057E-2, .3898194E-4,-.2959543E-4,-.5492775E-4,
P-.3474458E+1,-.2484927E-4, .3654421E-4, .9827073E+0,-.2147585E+1,
Q-.1078548E+0, .7978876E-3, .8899623E-4,-.3249739E-1, .5067226E-4,
R-.2651358E-2,-.7893836E-6, .2138504E-5, .1093593E-4,-.8047551E-3,
S-.1532810E-5, .4060731E-2, .1511806E-3,-.1593887E-3, .2311149E-6/

C

C 72HR ZONAL PREDICTOR NUMBERS ASSOCIATED WITH ABOVE COEFFICIENTS

DATA N72Z/

A	096,	129,	125,	080,	123,
B	037,	086,	022,	120,	112,
C	055,	142,	085,	122,	149,
D	143,	107,	158,	113,	165,
E	083,	166,	132,	020,	155,
F	163,	137,	073,	065,	148,
G	042,	068,	003,	108,	106,
H	072,	032,	054,	028,	012,
I	039,	074,	047,	161,	036,
J	006,	145,	164,	109,	146,
K	064,	057,	046,	069,	126,
L	048,	133,	013,	018,	104,
M	043,	076,	128,	088,	139,
N	041,	130,	034,	157,	131,
O	140,	025,	045,	016,	116,
P	084,	098,	103,	156,	150,
Q	114,	138,	117,	110,	095,
R	070,	011,	035,	134,	159,
S	031,	078,	121,	153,	021/

C

C 12 THROUGH 72HR ZONAL INTERCEPT VALUES

DATA CNSTZ/

\$-.67623E+3,-.91219E+3,-.13468E+4,-.16390E+4,-.96035E+3,-.13693E+2/
END

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SUBROUTINE STHGPR(XLATH,XLONH,BEAR,GRIDSZ,XI0,YJ0)
C  ALBION D. TAYLOR, MARCH 19, 1982
COMMON /HGRPRM/ A(3,3),RADPDG,RRTHNM,DGRIDH,HGRIDX,HGRIDY
CLAT=COS(RADPDG*XLATH)
SLAT=SIN(RADPDG*XLATH)
SLON=SIN(RADPDG*XLONH)
CLON=COS(RADPDG*XLONH)
SBEAR=SIN(RADPDG*BEAR)
CBEAR=COS(RADPDG*BEAR)
A(1,1)= CLAT*SLON
A(1,2)= CLAT*CLON
A(1,3)= SLAT
A(2,1)= - CLON*CBEAR + SLAT*SLON*SBEAR
A(2,2)= SLON*CBEAR + SLAT*CLON*SBEAR
A(2,3)= - CLAT* SBEAR
A(3,1)= - CLON*SBEAR - SLAT*SLON*CBEAR
A(3,2)= SLON*SBEAR - SLAT*CLON*CBEAR
A(3,3)= CLAT* CBEAR
DGRIDH=GRIDSZ
HGRIDX=XI0
HGRIDY=YJ0
RETURN
END

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      SUBROUTINE LL2XYH(XLAT,XLONG,XI,YJ)
C   ALBION D. TAYLOR, MARCH 19, 1982
      COMMON /HGRPRM/ A(3,3),RADPDG,RRTHNM,DGRIDH,HGRIDX,HGRIDY
      DIMENSION ZETA(3),ETA(3)
      CLAT=COS(RADPDG*XLAT)
      SLAT=SIN(RADPDG*XLAT)
      SLON=SIN(RADPDG*XLONG)
      CLON=COS(RADPDG*XLONG)
      ZETA(1)=CLAT*SLON
      ZETA(2)=CLAT*CLON
      ZETA(3)=SLAT
      DO 20 I=1,3
      ETA(I)=0.
      DO 20 J=1,3
      ETA(I)=ETA(I) + A(I,J)*ZETA(J)
20  CONTINUE
      R=SQRT(ETA(1)*ETA(1) + ETA(3)*ETA(3))
      XI=HGRIDX+RRTHNM*ATAN2(ETA(2),R)/DGRIDH
      IF(R.LE.0.) GO TO 40
      YJ=HGRIDY+RRTHNM*ATAN2(ETA(3),ETA(1))/DGRIDH
      RETURN
40  YJ=0.
      RETURN
      END

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      SUBROUTINE XY2LLH(XI,YJ,XLAT,XLONG)
C   ALBION D. TAYLOR, MARCH 19, 1982
      COMMON /HGRPRM/ A(3,3),RADPDG,RRTHNM,DGRIDH,HGRIDX,HGRIDY
      DIMENSION ZETA(3),ETA(3)
      CXI=COS(DGRIDH*(XI-HGRIDX)/RRTHNM)
      SXI=SIN(DGRIDH*(XI-HGRIDX)/RRTHNM)
      SYJ=SIN(DGRIDH*(YJ-HGRIDY)/RRTHNM)
      CYJ=COS(DGRIDH*(YJ-HGRIDY)/RRTHNM)
      ETA(1)=CXI*CYJ
      ETA(2)=SXI
      ETA(3)=CXI*SYJ
      DO 20 I=1,3
      ZETA(I)=0.
      DO 20 J=1,3
      ZETA(I)=ZETA(I) + A(J,I)*ETA(J)
20  CONTINUE
      R=SQRT(ZETA(1)*ZETA(1) + ZETA(2)*ZETA(2))
      XLAT=ATAN2(ZETA(3),R)/RADPDG
      IF(R.LE.0.) GO TO 40
      XLONG=ATAN2(ZETA(1),ZETA(2))/RADPDG
      RETURN
40  XLONG=0.
      RETURN
      END

```